Assessing flexibility, risk, and resilience in low-carbon power system planning under deep uncertainty

Report prepared for CSIRO and Global PST Consortium

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Executive Summary

The increasingly complex nature of numerous long-term uncertainties that could impact power system planning calls for considering new methodologies that may be able to propose more cost-effective and potentially less risky infrastructure investment and development paths. In this context, this project explores the value of adaptive, flexible planning methodologies in power system infrastructure investment, focusing on addressing long-term uncertainty, risk, robustness, and resilience. The core objectives that have been addressed during the project are organized into five groups:

A. Identifying optimal infrastructure investment solutions and optionality value with multi-stage stochastic planning.
B. Assessing the robustness of transmission plans based on deterministic approaches compared to flexible planning.
C. Quantifying investment risk associated with deterministic and stochastic methodologies and controlling investment risk.
D. Proposing methodologies to assess and quantify the value of different infrastructure investment options in providing resilience to High Impact Low Probability (HILP) events.
E. Preliminary assessment and comparison of the value of alternative technologies such as integrated electricity and hydrogen networks in long-term energy infrastructure planning.

A. <u>Flexible expansion plan based on multi-stage stochastic optimization</u>

This project delves into multi-stage stochastic planning for power system expansion under uncertain conditions, aiming to address the complexities associated with strategically expanding power systems. The stochastic planning model generally uses a scenario tree (see Figure 0.1) to capture the uncertainty in various parameters, such as load profile and evolution, renewable energy installed capacity, conventional generation unit decommission, technology investment various operation costs (e.g., associated with fuels), and so forth. Each node in the tree represents the operation and investment for a specific year, considering the uncertainty in the aforementioned variables. The expansion planning problem seeks to minimize the total expected costs associated with investment and operation decisions made in each node of the scenario tree. The optimization problem is subject to various constraints, including investment constraints (“non-anticipativity” and potential rules of investment across options), power system constraints (energy balances, reserve provision, power flow, and transmission limits), and unit-commitment constraints (including technical characteristics of conventional units).

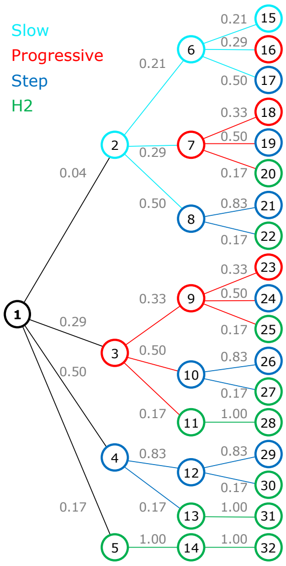


Figure 0.1. Scenario Tree

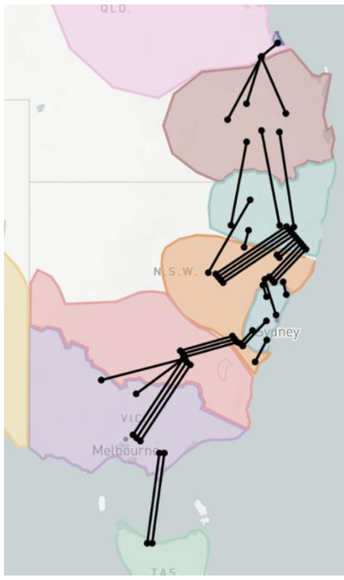


Figure 0.2. Transmission candidate investment options

The study utilizes data from the 2022 Integrated System Plan (ISP) developed by the Australian Energy Market Operator (AEMO) and covers a 20-year decision horizon (operation is modelled using 6 representative weeks per year with hourly resolution). It includes factors such as distributed energy resources, virtual power plants, grid-scale generation, energy storage systems, and electrification of transport. The ISP methodology models the future through a set of scenarios and sensitivities, aiming to find the least-cost development path for each scenario separately. It then identifies the least-regret development path across all scenarios using a least-worst weighted regret (LWWR) approach, taking scenario weights into account to reduce the impact of unlikely scenarios. The specific scenario tree adopted in the project to illustrate the different methodologies proposed was built upon the four scenarios used by AEMO in their ISP 2022. However, it should be noted that the aim of the project was not to compare results with those obtained by the ISP, also because only a few representative time series profiles were used, but rather to illustrate the features and potential benefits of alternative approaches.

The first part of the project focused on using data from the ISP 2022 to inform and validate the stochastic planning model previously developed by the project team at the University of Melbourne. This was then used to determine optimal portfolio of investment options using multi-stage stochastic optimisation for power system expansion under uncertain conditions. The core of the analysis was centred on the expected cost minimization considering decisions on new transmission investments (the 34 major candidate lines as described in the ISP 2022 are depicted in Figure 0.2), with some extensions to the co-optimisation of transmission and storage assets too. The results may be effectively illustrated via the cumulative probabilities of the total (investment and operation) cost across the different scenarios, as for instance shown in Figure 0.3. In this particular example, the optimal solution for the transmission-only instance resulted in a total expected cost of some $23 billion for 20 years of operation and investment in new transmission lines, as highlighted by the vertical dotted line in the figure.

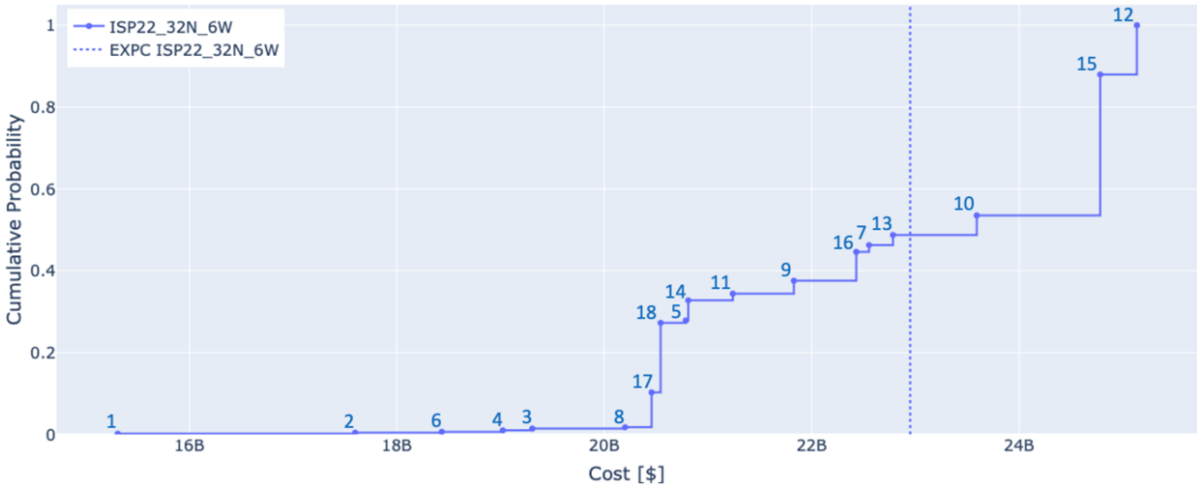


Figure 0.3. Distribution of total costs of operation and investment for each of the 18 scenarios included in the scenario tree

Key findings of the study include the identification of the backbone of the future network's reinforcement based on flexible investment options. The majority of investments aim to reinforce QLD and NSW internally and increase interconnection capacity between VIC and TAS. We also showed how the representation of operation in modelling affects the expected costs and optimal portfolio of transmission reinforcements. In particular, when fewer typical days or weeks are used to represent annual operation of the system, the resulting total investment and operation costs are substantially smaller. However, the resulting optimal portfolio performs very badly when tested against a larger representation of operations, suggesting the importance of suitably modelling representative operational conditions to develop robust infrastructure investment plans.

The case study incorporating additional (on top of the capacity considered in the ISP) battery energy storage systems (BESS) as an investment option resulted in a slightly lower expected cost, by some 0.3%, compared to the case without BESS investment options. However, the problem considering BESS investment took more than three times longer to solve.

In conclusion, the optimal transmission investment decisions are heavily influenced by the representation of operation and to a lesser extent by the inclusion of additional storage options.

B. <u>Deterministic planning</u>

Deterministic planning models are widely used in transmission expansion methodologies around the world. These models analyse various scenarios from a deterministic perspective. Some approaches then use an additional metric to select the optimal plan based on the results. Two deterministic-based metrics used by major system operators in the world, most noticeably AEMO in Australia and National Grid Electricity System Operator (ESO) in Great Britain, are Least-Worst Regret (LWR) and Least-Worst Weighted Regret (LWWR).

Originally adopted by National Grid ESO, LWR decisions use regrets, which indicate the difference between the cost of applying a specific portfolio of investment options and the reference cost, as a measure of proximity to the optimal solution. The methodology involves several steps: selecting scenarios and investment options, determining the optimal portfolio for each scenario, calculating the investment and operational costs, determining the specific development path that produces the lowest cost, calculating the regret for each development path, finding the worst (maximum) regret, and finally, selecting the development path with the least-worst regret. LWWR is a recently proposed variant of LWR, currently adopted by both AEMO and National Grid ESO, that incorporates scenario probabilities to account for different likelihoods of occurrence. This approach aims to include the impact of scenario probabilities in the LWR method, which otherwise assumes equal probability for all scenarios.

A quantitative comparison between LWR, LWWR, and a stochastic planning approach was conducted in the project for the first time. The study involves the disaggregation of a 32-node scenario tree into 18 deterministic scenarios. For each scenario, the optimal development path is determined using the same set of transmission investment options as for the stochastic problems. The cost matrix, which includes the investment and operational costs for each scenario and development path, is then calculated. Applying the LWR and LWWR metrics allows to identify the best development path resulting from the deterministic analysis of all scenarios, which turns out to be the same for both LWR and LWWR.

As pointed out before for the case study performed, the stochastic planning approach resulted in an optimal expected total cost of $23 billion over the next 20 years, while the deterministic-based approach using the Least-Worst Regret (LWR) metric identified a development path that had $1.5 billion higher expected total costs and a $4 billion more expensive worst-performing scenario compared to the stochastic approach. These results are depicted in Figure 0.4.

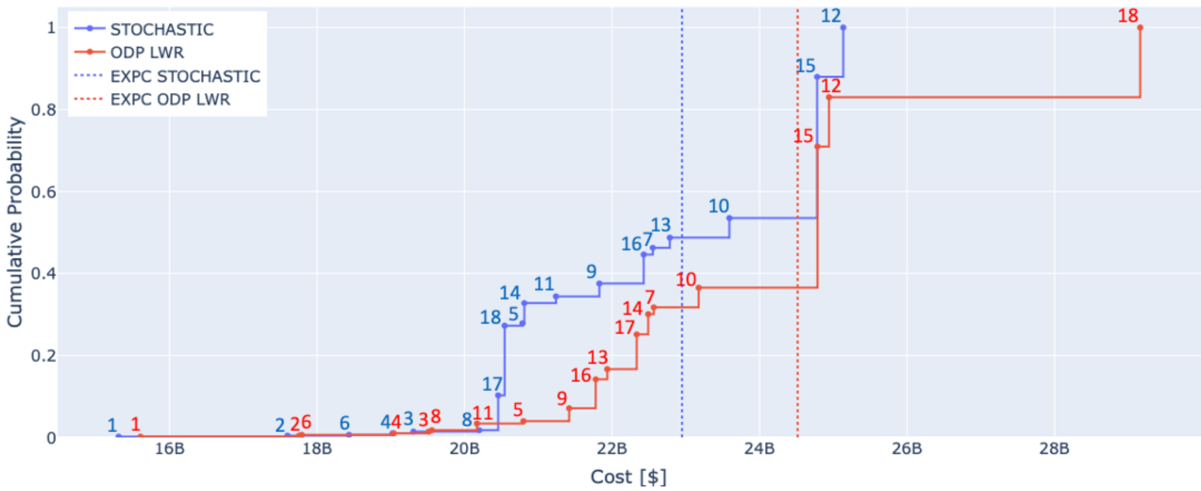


Figure 0.4. Comparison between optimal stochastic results and the LWR optimal development path (ODP)

The results demonstrate how the stochastic planning approach exhibits superior performance, relative to deterministic-based methodologies such as LWR and Least-Worst

Weighted Regret (LWWR), in addressing planning uncertainty. Minimizing the worst regret may lead to riskier portfolios compared to stochastic plans, suggesting that categorizing LWR as a risk-averse metric might only be appropriate in a deterministic context, while superior risk-hedge strategies could be identified through stochastic plans. The different objectives of each metric can result in significantly divergent investment strategies under conditions of profound uncertainty, as demonstrated in the case study discussed in this report. Overall, the results illustrate how a stochastic planning approach can provide a much more cohesive perspective across all future scenarios and hence devise development paths that are intrinsically both less expensive and less risky relative to an aggregate view across decisions performed over multiple independent deterministic scenarios.

C. Controlling the risk of the portfolio

The next part of the project aimed to highlight the importance of incorporating risk management principles when uncertainty is present in the process of defining the optimal portfolio of investments for the system. This is particularly important as risk assessment and analysis are not clearly modelled or even just captured in current methodologies. One of the ideas was also to study how while controlling expected cost and risk are generally competing objectives in portfolio optimization, introducing new investment alternatives, such as flexible technologies, could eventually reduce both expected costs and extreme outcomes simultaneously.

A risk-aware stochastic planning model was proposed, which includes a risk parameter (β) to represent different risk appetites. This model allows decision-makers to balance their position on risk, with a more *risk-averse* approach favouring risk minimization at the expense of increasing the expected total cost, while a *risk-neutral* approach focuses solely on minimizing expected cost. The use of such a risk parameter allows to determine efficient frontiers where each point represents the optimal balance of cost and risk, in turn enabling the definition of an optimal *risk-aware* portfolio for the system.

Understanding risk metrics is crucial for this process. Several risk metrics were discussed during the project, but the final analysis focused on what was deemed to be the most relevant metric in the context of the studies performed here, namely, the Conditional Value-at-Risk (CVaR). More specifically, while the Value-at-Risk (VaR) metric provides information about a predefined “worst-case” cost threshold (e.g., the 95% cost threshold across all scenarios), CVaR informs about the expected cost of those worst-case scenarios (e.g., the expected cost of the worst 5% scenarios), thus implicitly also providing information about their distribution. In fact, CVaR was preferred for its ability to identify low-probability but high-cost scenarios, making it an attractive risk measure for transmission expansion planning problems, especially where resilience against high-impact, low-probability events is also important.

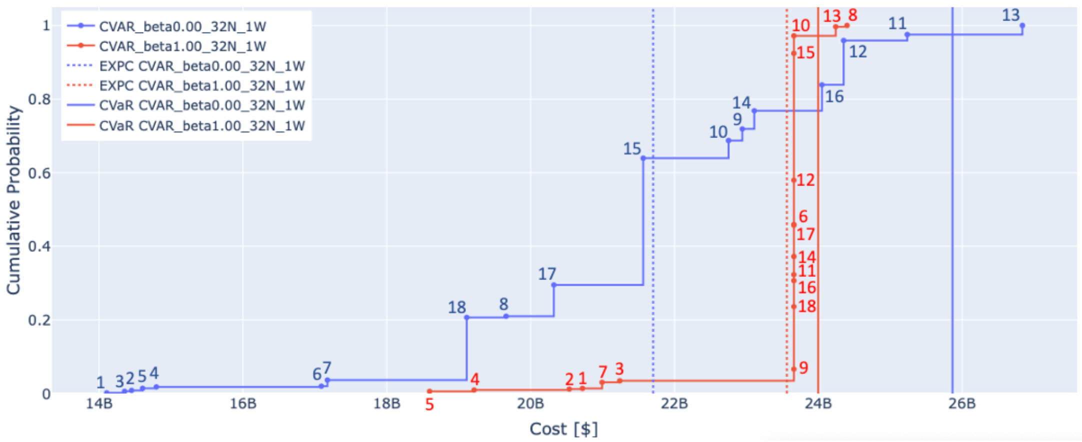


Figure 0.5. Distributions of total cost comparing the risk neutral (beta = 0, blue) and risk averse (beta = 1, red) cases

The case study carried out explored the impact of risk metrics on investment decisions using a CVaR-95% risk metric, which means that the expected value of the 5% worst-performing scenarios is considered. The study compares risk-neutral and fully risk-averse approaches and the distributions of results for each case are presented in Figure 0.5. The fully risk-averse approach (β=1) reduces the CVaR by $1.87 billion but also increases the expected cost by $1.86 billion. By exploring the efficient frontier (see Figure 0.6), the specific study finds that an intermediate risk-aversion would lead to a better trade-off, reducing risk by almost as much as the fully risk averse case ($1.868 billion), but with a smaller premium to be paid in terms of expected cost (only $0.3 billion).

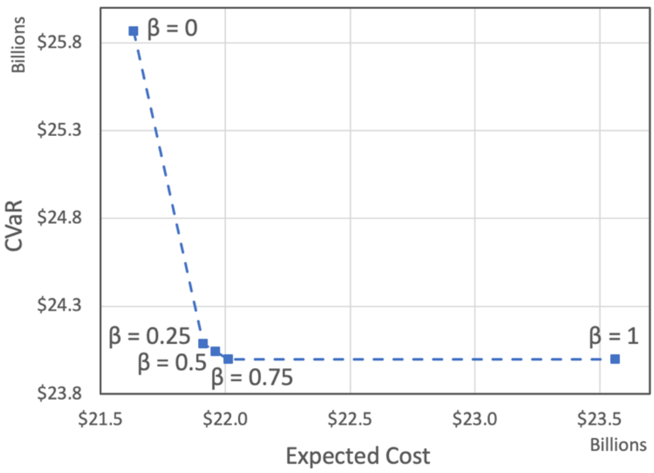


Figure 0.6. Efficient frontier for the case ISP22_32N_1W with CVaR-95% as risk metric

While the results here are purely illustrative, the efficient frontier analysis may be an important tool to explore the benefits of alternative investment options and their cost-risk implication. In this regard, a further study investigated the role of storage in risk-aware planning. By co-optimizing investment in storage along with transmission lines, the portfolio risk could be reduced by close to $140 million while only increasing the expected cost by close to $57 million. This additional storage helps accommodate more renewable energy, reducing operation costs and enhancing system performance in the most expensive scenarios, further reducing risk. This also suggests that the proposed risk-aware stochastic planning approach can be suitably adopted to reveal cost-risk trade-offs and benefits that integrated investment in a wide range of technologies (beyond transmission-only assets) could bring.

D. Methodologies to incorporate resilience analysis in stochastic planning

Extreme (weather) events affecting power systems have caused significant economic damage to the countries in which they have occurred, calling for a comprehensive understanding of their impact on power system infrastructure. Power system resilience, which refers to a system's ability to withstand, arrest and recover from high-impact, low-probability (HILP) events, recover quickly, and adapt for future events, has become a focal point for researchers and policymakers in the past few years.

Various frameworks, methodologies, and measures have been proposed to improve power system resilience, including stochastic optimization, hardening infrastructure, and risk aversion in network design and operation. In this context, in the project we proposed a set of resilience-oriented planning methodologies that could build on the stochastic planning framework.

Besides introducing different approaches to model high-impact low-probability events with different occurrence characteristics within scenario trees, as key part of the project three methodologies were proposed for studying the effect of extreme events in power system planning:

1. Risk-averse planning for resilience enhancement: This approach leverages the implicitly more robust investment portfolios identified by risk-averse planning to mitigate the risk of high-cost operational conditions that might emerge from the occurrence of extreme events, but without considering them explicitly in the planning.
2. Resilience-aware stochastic power system planning: This methodology explicitly represents high-impact low-probability events in the description of the system's future evolution by modifying the scenario tree structure. It shifts the focus from a reliability-oriented approach to a resilience-oriented one while still maintaining the constraints and considerations that guarantee reliability under expected conditions.
3. Two-step resilience-aware stochastic power system planning: This methodology (see Figure 0.7) involves two steps - first, planning the system for reliability using an adequacy and security standard approach, which results in the reliability-oriented portfolio. Second, high-impact, low-probability scenarios are overlaid on the original scenario tree to identify new optimal plans for the remaining transmission options, resulting in the resilience-oriented portfolio. A budget limit may also be included to ensure financial feasibility and justify additional assets and investment levels for greater resilience.

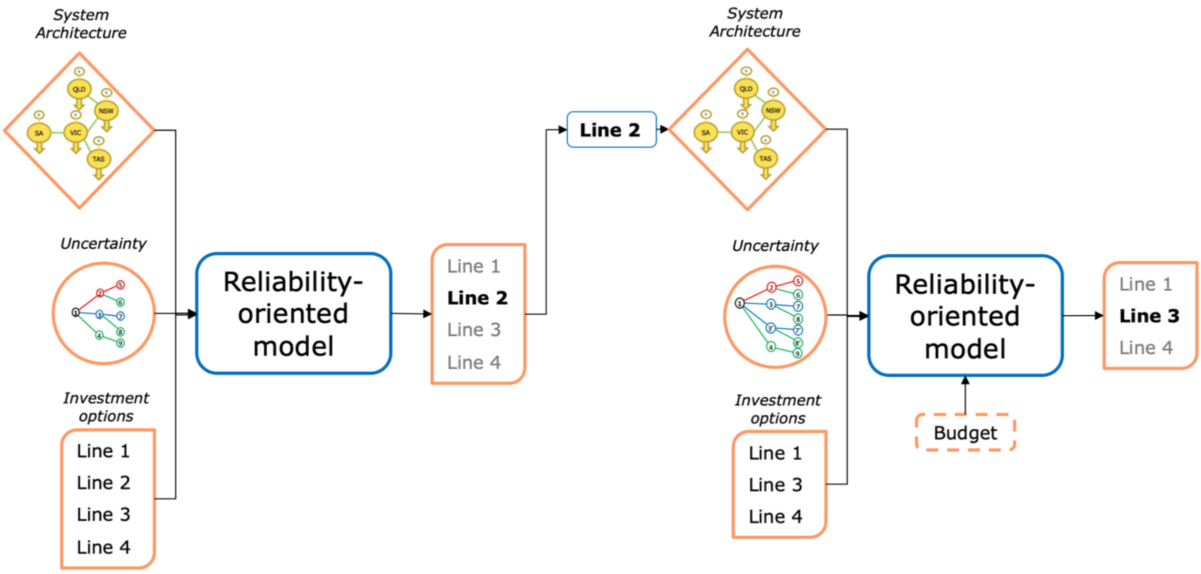


Figure 0.7. Illustration of the two-step methodology to determine resilience-oriented portfolios (methodology 3)

Various case study applications were considered to demonstrate the resilient planning methodologies proposed, including different HILP event occurrences within the scenario tree. The results show how incorporating resilience aspects into the planning approach can change the investment portfolios. Importantly, the stochastic planning approach can reveal the need for anticipative investments and early system reinforcements in anticipation of extreme events. Comparing stochastic planning to deterministic planning, more variation in investment decisions and greater flexibility can be recognised in the stochastic approach, while maintaining the expected costs relatively stable across different cases. This suggests that, in the context of formally introducing resilience in the planning exercise, the adaptable investments that stochastic planning naturally proposes could enable additional investments to protect the system in the face of extreme events, but without significantly increasing total costs.

A further dive-in on models and approaches that could be adopted to incorporate resilience into planning, and stochastic planning in particular, was also provided by the Electric Power Research Institute (EPRI), with focus on industry-oriented projects in the United States. The analysis performed by EPRI further underscores several key points, especially the importance of modelling in detail the characteristics of extreme events that may affect the system and the need to manage the computational complexity that might naturally emerge in this kind of studies. Overall, "planning for resilience" can still only be considered in its infancy, and substantial further research is needed on this topic in the future, especially for real-world practical implementations.

E. Role of hydrogen infrastructure

In the final part of the project, an integrated electricity and hydrogen transmission infrastructure planning model developed by the University of Melbourne team within the Future Fuels Cooperative Research Centre was used to quantify the impact of large-scale green hydrogen production on the investment planning. The modelling was assessed, as an *initial* proof of concept, on a case study consisting of proposed provisional corridors connecting renewable energy zones (REZ) and large hydrogen export demand in the superpower scenario of AEMO's ISP for the years (epochs) 2027, 2032, and 2037.

Under the cost and technical assumptions of the specific case study, looking into the most cost-effective *greenfield* infrastructure design that could connect REZ to large-scale green hydrogen demands, *preliminary* results show that hydrogen pipelines may generally be more cost-effective than their electricity counterparts under the specific corridor lengths and energy volumes considered. Specifically, the optimal solution, which consists of hydrogen pipelines exclusively as transport infrastructure, has a net present value (NPV) that is some 40% smaller than one with only HVAC transmission links and some three times smaller than one with only HVDC options. As the longest corridor is this greenfield case study has a length of 480km, these results are congruent with HVAC vs HVDC comparisons in existing literature, which identify a break-even distance of around 600km, beyond which HVDC becomes more cost effective. Overall, these initial results suggest that for envisaged developments of large-scale green hydrogen demand hubs, hydrogen pipelines may merit consideration alongside electricity corridors to achieve an overall cost-efficient whole-system planning. Nonetheless, these *preliminary* findings in this part of the project are not intended to provide recommendations for AEMO to co-optimise electricity and hydrogen infrastructure networks. More rigorous studies are needed to better quantify the value of including hydrogen pipeline options in the co-planning enterprise.

Acronyms

AC	alternating current
AEMO	Australia Energy Market Operator
BESS	battery energy storage systems
CAISO	California Independent System Operator
CBA	cost-benefit analysis
DER	distributed energy resource
DSM	demand-side management
EHB	European hydrogen backbone
FFR	fast frequency response
GB	Great Britain
HHV	higher heating value
HILP	high impact and low probability
HSC	hydrogen supply chains
HVAC	high-voltage alternating current
HVDC	high-voltage direct current
ISO	independent system operator
ISP	integrated system plan
LCOE	levelised cost of energy
LOHC	liquid organic hydrogen carriers
LWR	least-worst regret
LWWR	least-worst weighted regret
MILP	mixed-integer linear programming
MISO	Midcontinent Independent System Operator
NEM	National Electricity Market
NGESO	National Grid Electricity System Operator
NOA	network options assessment
NPV	net present value
OHL	overhead line
PEM	proton exchange membrane
PFR	primary frequency response
PJM	Pennsylvania New Jersey Maryland Interconnection LLC
PV	photovoltaic
PtG	power-to-gas
RES	renewable energy sources
REZ	renewable energy zones
ROCOF	rate of change of frequency
SFR	secondary frequency response
TEP	transmission expansion problem
UC	unit commitment
VRE	variable renewable energy
VSC	voltage-source converter

Table of Contents

1 Introduction

1.1 Context

The uptake of large-scale and distributed renewable energy sources (RES) and the electrification of different sectors in power systems around the world are producing massive changes and creating unprecedented operational and planning challenges. In particular, there is increasing uncertainty as to what new network users will connect to the system, and when and where. As envisaged by the recent integrated system plan (ISP) [1], some scenario with large-scale adoption of hydrogen technologies for clean fuel export might even lead to a complete transformation and upsizing of the energy system. Planners are thus required to perform the daunting task of striking a balance between ensuring security and reliability and minimising cost while facing very large long-term uncertainty.

Major open research problems of high immediacy are the development of risk-aware planning methodologies and metrics to deal with the challenges associated to large-scale, long-term uncertainty. Practical steps in this direction have already been undertaken by a few system operators, most noticeably the National Grid Electricity System Operator (ESO) in Great Britain and AEMO here in Australia, through the adoption of metrics such as least-worst weighted regret (LWWR) [1]. An even more powerful approach would consider to make decisions in a fully stochastic setting, where adaptive and flexible decisions could enable the decision maker to better respond to unfolding uncertainty, enhance the control and minimise the investment risk introduced by some scenarios, and reveal the full "option value" of proactive or delayed investments.

In this project, supported by UoM's stochastic planning methodology and tool, we aim to study the representation of long-term uncertainty and how investment flexibility resulting from the stochastic approach further decreases the planning risk, how and why the results from a flexible plan stemming from stochastic analysis would differ from more established approaches such as LWWR, how HILP events could be incorporated into planning and how the resilience value of different investment options could be assessed, and the role and value of operational flexibility options such as based on Distributed Energy Resources (DER) and hydrogen-related assets. In doing so, UoM will also be supported by the Electric Power Research Institute (EPRI), particularly to receive inputs and feedback from their planning work with different utilities in North America and worldwide and to jointly propose suitable methodologies to assess the value of different infrastructure options to provide system resilience.

1.2 Aims and objectives

This project aims to study the value of an adaptive, flexible planning methodology in improving the robustness and assessing the risk of infrastructure investment decision making by adequately modelling deep long-term uncertainty relative to more established approaches used by system operators based on deterministic approaches. The analysis also includes exploring suitable methodologies to incorporate resilience to extreme events in planning. These tasks can mainly be framed within research programme 1 “Long-term uncertainty” as described in [2], also interacting with several project in research programme 4 “Decision-making”.

The core objectives of the project are organized in 5 groups, which are addressed in the same order in this report:

A. Identify the optimal infrastructure investment solutions, and their optionality value, yielded by an adaptive, flexible plan based on multi-stage stochastic planning.
B. Assess the robustness of a transmission plan based on deterministic approaches such as least-worst weighted regret (LWWR) analysis relative to flexible planning.
C. Quantify the investment risk associated with deterministic and stochastic methodologies and possible options to model and control investment risk.
D. Propose suitable methodologies to assess and quantify the value of different infrastructure investment options in providing resilience to HILP events.
E. Assess and compare the value of investment in alternative technologies, like DER and hydrogen as a means to defer investment-intensive assets.

In the context of [2], Figure 1.1 depicts the completion stage of each relevant research activity covered by the end of this project.

PROGRAMME	STREAM	PROJECT	CODE	Project	Progress
Long-term Uncertainty	Scenario development for planning studies	Modelling long-term uncertainty in power system planning with the consideration of HILP events (adequacy and security) and critical operation conditions	R1S1P3	Ongoing	15%
Decision Making	Metrics, objectives and risk modelling of different stakeholders	Modelling competing objectives, sources of risk, and risk appetite of different stakeholders in power system planning. Determination of metrics to value cost and risk	R4S1P1	Ongoing	25%
		Modelling investment flexibility in power system planning decision making by enhancing the decision structure and the representation of scenario trees	R4S2P2	Ongoing	50%
Distributed Energy Systems	Multi-energy systems	Modelling the impact and flexibility embedded in the interactions between power systems and other energy systems for planning studies	R5S1P1	Ongoing	10%

Figure 1.1. Expected progress for the research activities considered in the initial research plan by the end of the current ongoing project.

This document also presents a review of literature and industry practices on the different objectives described before. The literature review includes the following aspects:

- the review of scholarly body of knowledge on new advancements in planning methodologies to address the challenges faced by system operators around the world
- a review of industry practices in different jurisdictions worldwide, highlighting their considerations behind the representation of uncertainty and the main components of their transmission investment methodologies

- an assessment of the new methodological developments to include resilience[1] within power system planning approaches, and
- a review of recent efforts to consider hydrogen assets in the portfolio of expansion options in power system planning.

1.3 Report Structure

Section 2 presents a review of the literature about planning methodologies, the current efforts in the realm of resilience considerations within power system planning and the development of hydrogen infrastructure within power systems. Section 3 describes the theoretical foundations of the model used in this work, the input data that is used to build the case study applications and introduces the results for the base cases that are used in the different sections of this report. Section 4 presents and discusses the differences between deterministic and stochastic planning approaches, highlighting their effects on the portfolios found by each methodology. Section 5 analyses the effect of controlling risk within a stochastic planning framework. Section 6 discusses potential methodologies to introduce resilience criteria in the stochastic planning framework. Section 7 examines approaches and relevant considerations to include hydrogen infrastructure planning as an alternative to the traditional deployment of transmission lines to transport bulk energy across the system. Section 8 delivers the main conclusions of this work.

[1] CIGRE defines resilience in power systems as the "*Ability to limit the extent, severity and duration of system degradation following an extreme event".*

2 Literature review

2.1 Power system expansion planning

2.1.1 General overview of power system expansion planning

In general, the possibility to represent the expansion of the system under uncertainty through a monolithic or deterministic equivalent problem is limited due to the large number of competing investment options, uncertain variables, and the need of representing the operation of the system with high levels of detail. Despite the great advances in off-the-shelf optimisation software and high-performance computing, the computational requirements of this problem impose the need to use decomposition techniques to address the challenge. In this section the state-of-the-art in these topics is presented.

A key concept behind the discussion of power system expansion planning is investment flexibility, which corresponds to the capacity of investment options to add value to the system across different scenarios. The work in [3], [4] discusses this concept with special focus on how to adequately represent the uncertainty and investment decisions to capture that flexibility. One fundamental aspect of capturing investment flexibility is the representation of the operational flexibility of the different assets, either existing or candidate assets. Flexibility in operation can only be assessed if the underlying operational model is able to represent the limitations and strengths of the different units, for instance, specific technical constraints of thermal synchronous units. Understanding the impact of different models of operational flexibility in the expansion planning model has been addressed by multiple authors in the past. The authors in [5], [6] investigate the impact of operational flexibility in the design of a generation portfolio and [7]–[11] also aim to model operation flexibility to describe the appropriateness of investing in transmission and storage assets. It is clear that, in an attempt to capture more operation flexibility, a price is paid in computational burden due to the need to have a more detailed operation of the assets (more constraints) and/or a denser representation of the operation (more variables). The work in [12] utilises multi-cut Benders' decomposition to assess the impact of unit commitment (UC) constraints in a two-stage generation expansion problem. Various reviews [13]–[16] on expansion planning highlight multiple works that describe -among other things- different approaches to account for operational flexibility in generation and transmission expansion modelling.

Another source of complex operational constraints corresponds to the case of expansion planning of storage, transmission and generation assets with the consideration of frequency security constraints that can differentiate among frequency response resources, namely, inertia, fast frequency response (FFR), primary frequency response (PFR), secondary frequency response (SFR), among other frequency service denominations. The work in [17] introduces a generation expansion model that considers the effect of inertia and PFR to limit frequency nadir. The model does not consider the effect of the natural frequency response coming from demand, or the effect of FFR in the allocation of frequency response resources, however it does consider the risk observed for each portfolio using conditional value-at-risk (CVaR) as metric. The authors in [18] consider the demand damping factor in the frequency response constraints including inertia and PFR in the context of a generation expansion planning. Recently, [19] proposed a generation expansion model that considers unit commitment constraints, a second-order cone approximation of the AC optimal power flow, and introduces inertia requirements via rate of change of frequency (ROCOF). The work in [20] presents a model capable to expand generation considering a generalised N-1 security criterion which allocates droop-controlled response, but it fails to consider inertia which limits the capacity to account for frequency extrema requirements. As seen here, it is possible to say that the expansion planning of low carbon power system with consideration of fast frequency response resources remains broadly unexplored. In general, new challenges in power systems, such as system strength issues and reactive power provision, coupled with emerging technologies like electrolysers, add complexity and bring about additional modelling challenges for power system analysis overall, and specifically for power system investment planning.

Including complex operational constraints in a highly detailed model of the operation of the system, in the context of the expansion planning under uncertainty, creates a very large monolithic problem. Different works on stochastic planning models have relied on advanced decomposition techniques to overcome intractability of large MILP models. Recent work on Dantzig–Wolfe decomposition and column generation-based algorithms have provided an approach to handle the size of this problem. A multi-stage stochastic capacity problem is solved by applying a “variable splitting” technique in the column generation algorithm [21]. In [22], UC constraints have been incorporated in the operational problem for solving a generation expansion problem, in [23] the same is done for the expansion of transmission and storage assets applied to a real instance of the Australian power system, and in [24] gas network constraints have been integrated into a stochastic planning problem. A welfare-maximising approach for transmission capacity expansion considering an oligopoly where the companies compete on the amount of output (in this case transmission capacity) using column generation to solve the problem is presented in [25]. In [26] authors underscore that developing computationally efficient methods to address non-convexities when considering high operational details in planning is an important research avenue to be able to fully capture the benefits of smart grid technologies in real-size planning problems.

Although effective in dealing with the size challenges, the column generation algorithm usually displays three important issues: slow convergence during the final iterations, commonly known as tailing-off effect; the plateau effect, which describes the process in which the master problem solution value remains relatively constant for several iterations, and the bang-bang effect, a source of instability in the convergence process, where the dual solutions jump from one extreme to another, slowing down convergence [27]. Different methods [28]–[30] have been applied to tackle these effects, which in general involve restricting or relaxing the master problem.

2.1.2 Uncertainty in electrical power system Transmission Expansion Planning (TEP)

2.1.2.1 Uncertainty sources

When dealing with long-term planning of power systems it is of upmost importance to identify the sources of uncertainty that will condition the needs of the system. Any power system is heavily influenced by changes in energy policy, development of new technologies and evolution of new business models. All these lead to high and growing uncertainty. This section reviews the main uncertainty sources influencing transmission expansion planning (TEP). CIGRE's review on uncertainty in optimal power system planning [31] is the starting point of this analysis. More uncertainty factors can be considered in specific system, but the list is otherwise comprehensive in the factors that most influence planning decisions.

1. **Load growth:** Uncertainty in demand growth has been traditionally one system planners' main concerns. In fact, most planning methodologies already include some level of uncertainty in demand. Currently, demand patterns are expected to change due to electrification of end-uses (e.g., cooking, heating) and the appearance of new technologies (i.e., electric vehicles, electric heat pumps). Furthermore, these new technologies can potentially be responsive to system conditions through demand side management (DSM), distributed storage, etc. In this context, there are high levels of both short-term (e.g., higher variability and uncertainty, price-responsive demand) and long-term (e.g., levels of electrification of other sectors, energy efficiency measures) uncertainties associated with the demand side.
2. **RES growth**: The penetration level of renewable energy sources is increasing in the system due to energy policies and cost reduction, especially in the case of Distributed Energy Resources (DER), which has changed the traditional view of the distribution network as a passive network. These new elements need to be included in both network operation, considering the increase in variable and partly unpredictable and non-dispatchable generation, and therefore increasing operational uncertainty, as well as network planning, considering the uncertainty in volume, location and timing of RES connection.
3. **Commercial technologies**: Traditionally, power systems have required high investments and considerable lead times to implement network changes. Nevertheless, new technologies (i.e., DSM, battery storage, etc.), can result in lower investment costs and shorter lead times compared to traditional infrastructures. However, they are characterised by cost functions that are largely based on operational cost (which are typically uncertain) rather than investment costs as for traditional asset. This creates issues in how to compare these two types of assets (traditional investment-heavy infrastructure with relatively small operational costs

and low-investment asset with considerable operation costs associated with the availability and activation of the corresponding commercial strategy), also considering that, depending on the regulatory framework, new technologies may not belong to or be operated by the system operator.

4. **Regulatory and energy policy environment**: Energy policy and regulation are currently under continuous revision in most countries, being a great source of long-term uncertainty. A few of the most remarkable ways in which regulation and policy might affect power systems are the following:
    - Influence the cost of certain technologies by directly supporting their development using subsidies or by taxing other technologies. For instance, subsidies to promote residential PV are a common practice in many regions of the world.
    - Introduce new schemes which affect the paradigm of the sector. For instance, enforcing the consideration of environmental issues, promoting the development of certain regions, addressing social license issues, or considering interconnection objectives with other countries.
5. **Electricity markets and regulation**: Closely related to energy policy, in regions with high decarbonisation targets there is an ongoing revision of power market structures and mechanisms that can have crucial effects on economic dispatch and power flows. Furthermore, new technologies have triggered the appearance of new markets, which are currently under study. For instance, the increase of renewable penetration level and the full retirement of coal plants by 2025 is challenging NGESO to fulfil its role of reliably operating the GB power system. However, the GB electricity wholesale market does not offer enough incentive to build relatively low-carbon conventional generators, e.g., combined cycle gas turbines and biomass plants, which are required to enable adequate reserve margin in winter peak periods. Therefore, a capacity market mechanism has been introduced to give extra financial support to peak capacity contributor since 2014 [32]. Similar challenges are being faced in other jurisdictions worldwide, for example in Australia.
6. **Generation mix**: Changes in the generation mix are a source of long-term uncertainty as well. As has been mentioned throughout this section, new technologies have emerged and are being introduced with high penetration in power systems worldwide, changing the generation mix in most regions. This change may be driven by policies (e.g., subsidies for renewables), extreme events (e.g., catastrophic events leading to closure of nuclear generation), new ancillary services requirements in the presence of renewables and asynchronously connected resources (e.g., requirements for faster frequency response and minimum system inertia), etc. However, not only new technologies drive the uncertainty of the generation mix: for example, the timing of synchronous unit decommitment is both highly uncertain and critical to

determining what the optimal investment portfolio is for the current and future network.

7. **Investment cost**: Uncertainty in (reduction of) investment costs of new technologies greatly influence investment decisions, as it might change the optimal investment option (both in resource portfolios as well as in assets to facilitate the development of new resources) in a few years. For instance, the cost reduction of new technologies such as high voltage direct current (HVDC) might lead to a totally different optimal design of reinforcement. The substantial cost reduction of renewable generation and batteries could also substantially impact the planning exercise.
8. **Weather and climate change:** is a major challenge on the horizon. The changing climate means power systems are impacted by increasingly severe and frequent extreme events such as heatwaves, wildfires, and freezing temperatures. Low water availability, both for hydropower generation and for cooling in thermal generation is another, more persistent effect that is becoming more common as the climate changes. Transmission planners increasingly need to anticipate multi-contingency events caused by climate uncertainty, rather than the random failures of one or two components.
9. **Fuel prices and availability**: particularly natural gas, is another major source of uncertainty. The price of gas determines the economic dispatch of generation, which in turn influences the operating flexibility of the system. Disruptions to the fuel supply, pipelines, or storage facilities create contingencies that transmission can possibly alleviate, so planners have given additional focus to gas price sensitivity.

Hence, in this rapidly evolving and highly uncertain context there are several opportunities but also risks. Planning the electricity network using a modelling framework capable of considering all these uncertainties is therefore key to providing cost-effective solutions.

2.1.2.2 Uncertainty factors in TEP

As mentioned above, there are nine key uncertainty factors that have been identified in the TEP process. Based on [1], [33]–[42], which describe the current TEP practices of seven countries across five continents, Table 2.1 summarises the uncertainty factors currently being considered or which are material but are not considered by corresponding network planners.

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

As for **generation mix**, this uncertainty factor has been widely acknowledged by all nine network planners that have been reviewed. The Australian Electricity Market Operator (AEMO) and EirGrid have made relevant considerations on the impact of evolving generation mix, e.g., by setting new frequency response requirements and inertia constraints, limiting the maximum output of a single generator in reducing contingency size, etc. National Grid has also begun to assess the impact of increasing renewable penetration by including ROCOF in its economic dispatch modelling. MISO has recently completed its renewable integration impact assessment (RIIA) which is among the most comprehensive studies to date investigating the complexity of renewable integration [43]. Among the major findings of RIIA is that the complexity of renewable integration increases rapidly after 30% penetration as new risks are created and the important periods of grid stress shift and become more severe.

With regards to **new technologies and commercial solutions**, such as batteries and demand response, although there are relevant technology deployments in France, UK, Australia and Ireland, these alternative options are just starting to be considered systematically in transmission network planning to defer or avoid investments of traditional infrastructures (i.e., power lines, substations, etc.). The Pennsylvania-New Jersey-Maryland Interconnection system operator (PJM) in the US, however, is shifting to treat storage as a transmission asset and has developed effective load carrying capability (ELCC) ratings for intermittent resources, storage, and hybrid facilities to reflect the value of storage in managing the hourly loss of load probability (LOLP) profile [44]. The Midcontinent Independent System Operator (MISO) examines storage and demand response extensively, along with reliability and market implications, in the RIIA report, and California's Independent System Operator (CAISO) has initiated a special study for the 2022 cycle to examine high electrification policies [45].

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

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

With regards to the uncertainty embedded in **energy markets and regulation**, National Grid, AEMO and EirGrid simulate wholesale and balancing services market operation by implementing, with different levels of approximation, dispatch and redispatch processes and bidding behaviour in their operational model, which gives their network planning process the capability to capture the potential impact of market changes. In contrast, CAISO conducts sensitivities for its energy imbalance market, but given the complexities of interregional cost allocation, and the flexibility market participants having to leave the market, CAISO recommends against using market effects to justify projects [46].

Weather and climate change can impact several aspects of future operation of power systems. Chile, Australia and MISO already consider different scenarios for hydro inflows available for hydro-power generation. Other aspects of the power system can be affected due to increasing temperatures, for instance, efficiencies of energy generation units (thermal, PV, etc.) will decrease as temperature increases.

Fuel prices represent an important source of uncertainty in power system planning. In general, all planning methodologies under consideration in this review consider future fuel prices as a relevant component of uncertainty to be represented in the different scenarios. Only China does not consider it as an uncertainty factor. Recent events associated to the Russian-Ukrainian conflict have shown how critical fuel prices can become in the operation of a power system, which ought to be considered in the context of transmission planning.

Table 2.1. Uncertainty factors of TEP considered by different transmission network planners ([33]–[42], [47], [48]*)*

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

Country	Uncertainty factor								
	Load growth	**RES growth**	**Generation mix**	**New commercial solutions**	**Technology Investment cost**	**Regulatory environment**	**Energy market and regulation**	**Weather and climate change**	**Fuel prices**
France (RTE)	✓	✓	⊕	⊕	⊕	✓	⊕		✓
China (State Grid)	✓	⊕	⊕		✓			⊕	
UK (National Grid)	✓	✓	⊕	⊕	⊕	✓	✓		✓
Chile (CEN)	✓	✓	⊕		⊕	⊕	⊕	✓	✓
Australia (AEMO)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ireland (EirGrid)	✓	✓	✓	⊕	⊕	✓	✓		✓
US (PJM)	✓	✓	✓	✓		✓	✓	⊕	✓
US (CAISO)	✓	✓	✓	✓		✓	✓	✓	✓
US (MISO)	✓	✓	✓	✓	✓	✓	✓	⊕	✓

2.1.2.3 Modelling Uncertainty through Scenarios

Scenarios allow planners to model different evolution of uncertain variables as well as their correlations. This strategy is preferred in most decision-making problems that tackle planning, as it provides a balance between analysing a broad range of futures and (technical) detail in such analysis. Furthermore, they can be applied to some of the most common methodologies used in decision making, including, potentially, methodologies based on probabilistic approaches (in which scenarios have specific associated weights). Scenario analysis or “scenario-based” approach is currently used by most system planners around the world to model the uncertain future [34].

The number of characteristics of scenarios used in the selected countries are listed in Table 2.2. It can be noticed that most planners prefer to use less than five scenarios to represent plausible futures, e.g., envisaging nuclear or coal plants retirement, increase of DER penetration, electrification of heating and transport, etc.

In some cases, the system planner builds scenarios or performs further studies to represent (technical and economic) sensitivities around core scenarios. For example, AEMO has developed 12 additional sensitivities around its scenarios to represent possible important opportunities/risks in the future [1]. Terna, the system operator in Italy, also uses two extra scenarios to represent sensitivity of potential futures rather than the expected future [49]. National Grid is currently using a probabilistic load flow approach in the security assessment of the “Two Degrees” scenario, to add robustness in the analysis of the boundary transfer capability with/without proposed reinforcements, as this scenario is considered as the one with highest network stress among all four scenarios. In Swissgrid’s Strategic Grid 2025 proposal [50], two marginal scenarios, “Sun” and “Stagnancy”, are built to check the long-term robustness of reinforcement options proposed in the two core scenarios, whilst the two marginal scenarios are not used to identify any additional network reinforcement requirement.

MISO has created three futures [51] which it uses across its planning studies including the regular transmission planning cycle [52], the long-range transmission plan (LRTP) studies [53], and the renewable integration impact assessment (RIIA) [43]. These studies each include their own sensitivities. RIIA, for instance, includes milestones for each 10% increment of renewable integration, with additional sensitivities for the type and geographic distribution of renewable generators. The long-range transmission plan (LRTP), aimed at finding a tranche of multi-value projects in the 20-to-40-year horizon, includes further sensitivities into higher gas prices.

CAISO, in addition to its standard sensitivities [46] of load, hydrological conditions, and gas prices, conducts special studies to explore relevant scenarios in more detail. These include the out of state wind study and the offshore wind study in the 2021-2022 cycle [54], the high electrification future study and the reduced gas storage study in the 2022-2023 cycle [55], and the 20-year transmission outlook study [56]. The number of these new sensitivity studies varies as not issues are identified as needing further study. Often, the key details of such studies are incorporated into the normal planning process rather than maintaining the study as a standalone sensitivity. PJM follows a similar approach to CAISO by including key sensitivities in the normal planning cycle [57], and conducting special studies on specific issues that are identified, such as the offshore wind integration study [44]. But because the PJM grid is largely filled out, such projects do not impose the same challenges and are simpler to conduct compared to CAISO and WECC.

Given the complexity of both technical and economic analysis associated with scenario-based planning, as well as the unfolding of uncertainty, some system operators have also envisaged to reduce the number of scenarios that are considered in the process. For example, the Chilean ISO has decided to decrease the number of scenarios from five to three from 2020, while EirGrid has removed the “Slow-Progress” scenario from its Tomorrow’s Energy Scenarios 2019 [35].

As an important point to note, of the planning organisations listed in Table 2.2, AEMO [1] and MISO [58] explicitly consider weighting scenarios in their CBA process [58], and NGESO does consider the use of weights in specific parts of the NOA process [39]. [58]Stakeholders provide weights based on their views about the likelihood of each scenario, and MISO uses these weights to combine the scenario-specific costs and benefits into a probabilistically weighed cost-benefit ratio [59]. And while the other ISOs and RTOs do not conduct probabilistic planning studies, they do occasionally partner with universities to conduct such studies, with WECC being a notable example [60], [61]

Table 2.2. Number of scenarios used in transmission planning in ten selected countries ([1], [33]–[35], [37], [38], [40], [44], [46], [49], [50], [56], [62], [63]*)*

UK	France	China	Chile	Australia	Ireland	Switzerland	Belgium	Germany	Italy	PJM	CAISO	MISO
4	3	1	3	4+12	3	2(4)	3	3	1+2	5	>3	3+11

2.1.3 Industry practices

Other than identifying existing uncertainty factors and scenarios in several countries, the technical details of the TEP models used by the seven selected countries already discussed above are listed in Table 2.3. The table is divided into four sections, which follow the methodology of TEP explained for the NOA process in [39] which is considered common practice worldwide. More specifically, the economic and security zonal boundary analyses are first performed to identify additional power flow requirements in order to avoid network congestion in the future. Then, candidate reinforcement options are tested with different security constraints (e.g., steady-state thermal and voltage limits). Finally, reinforcement options are applied in the operational model to generate system operational cost in the relevant scenarios, whose results are then fed into the CBA process to determining the best option for reinforcement.

As shown in Table 2.3, the **planning horizon** is generally in the range of 15 to 20 years, except for Swissgrid and CAISO which only define a transmission expansion plan for the next 10 years. However, Swissgrid would then perform a technical analysis against the robustness of its reinforcement options for a 20-year horizon, and CAISO conducts a separate 20-year transmission outlook study to explore grid requirements and coordinate with other entities over a longer time horizon [56].

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

For the **security assessment of boundary transfer capability**, there are countries which perform more than a winter peak snapshot analysis. For example, Chile not only performs Winter/Summer peak snapshots, but also analyses specific snapshots that are likely to be associated with maximum levels of power transfer across relevant boundaries.

With regards to the **security assessment of the combination of reinforcement options** shown in Table 2.3, most countries prefer to perform the analysis at various demand levels to mimic different system operating condition besides the peak snapshot. In addition, National Grid's NOA comprehensively covers network security criteria in the analysis. On the other hand, other ISOs perform extra tests such as reactive power management and frequency stability assessment, like in the case of AEMO. MISO not only selects the summer and winter daily peaks, but also the night-time peaks to monitor the system without solar and with different load patterns; MISO also uses snapshots from the shoulder seasons to explore thermal, voltage, and dynamic stability issues with minimal thermal availability for reactive support and with different renewable dispatches [52]. CAISO uses various off-peak and renewable snapshots, as well as dry hydrological conditions and extreme event contingencies such as those caused by heatwaves or wildfires [54]. And PJM includes contingencies for natural gas pipeline failures that could result from cyber-attack or natural disasters [44].

For the **operating cost assessment of reinforcement options**, which is used in CBA process, different countries use different sampling period varying from 2-3 years by National Grid up to 10 years by State Grid and Swissgrid. Additionally, with regards to the modelling of system operation, some countries use simple economic dispatch, while other countries adopt unit commitment analysis to better capture the technical characteristics of conventional generators (minimum up- and down-time, start-up/shut-down activities, etc.). The technical constraints of system operation also vary in the simulation performed by different planners. In terms of *modelling of the network*, the maximum flows of individual transmission lines are typically calculated according to thermal, voltage and fault-clearing standards, then the results are mapped as numerical constraints in economic-dispatch/unit-commitment. However, static transfer capability is used by State Grid in its economic dispatch process. With regards to *ancillary services*, most countries model these as “lumped” spinning reserve through derating online plant capacity, while AEMO also models the requirement of minimum inertia level due to ROCOF, which can be crucial for low-inertia system operation.

Most importantly, for **investment decision-making tools**, only a few planners (NG, MISO, CAISO) use LWR. MISO uses a probabilistically weighted benefit to cost ratio in a normal planning cycle and the least regret approach to identify projects in long-range transmission planning studies [58], [59]. CAISO uses a least regret approach to identify projects that best balance several objectives, such as cost and renewable integration policies [46]. Other countries use deterministic approach to obtain the best reinforcement option that brings net present value (NPV) maximisation in each scenario. However, from the review conducted it is unclear how a final, integrated decision across scenarios would be made.

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

Table 2.3. International practice of technical modelling characteristics in TEP process ([1], [33]–[39], [49], [50], [62]–[66]*)*

Simulation Stage	Features	Countries/Jurisdictions									
		UK (NGESO)	**France (RTE)**	**China (State Grid)**	**Chile (CEN)**	**Australia (AEMO)**	**Ireland (EirGrid)**	**Switzerland (Swissgrid)**	**US (PJM)**	**US (CAISO)**	**US (MISO)**
Planning horizon (years)		20	15	15	20	20+	20	10(20)	15	10 (20)	20+
Zonal boundary assessment (Economy)	**Software**	PLEXOS	ANTARES	SPER	AMEBA	PLEXOS	*Not available*	N/A	PROMOD	ABB GridView	PROMOD, PLEXOS
	Resolution and timescale	3-6h (up to 1 hour); whole year	Hourly; whole year	15 mins to hourly; typical day in each month	Few hours (8 blocks per day); typical weekday/ weekend in each month	Few hours (few load blocks); from snapshot to whole year	Hourly; whole year		Hourly; whole year	Hourly; whole year	Hourly; whole year
Zonal boundary assessment (Security)	**Software**	POUYA	CONVER-GENCE	PSD-BPA	Powerfactory	PSS/E	PSS/E, DSA		PSS/E, TARA	GE PSLF, PowerGem, TARA	PSS/E, POM, TSAT, TARA
	Timescale	Winter peak snapshot	Snapshots	Typical snapshots	Winter / summer and transfer peak snapshots	Multiple Snapshots	Peak and other demand snapshots		Summer / winter peak, light load + high wind	Peak Load, Net Peak Load, Off peak	Summer / winter peak, Light load, Shoulder load
	System condition	N-1	N-1	N-1	Intact/N-1	*Not available*	N-1		N-1	N-1	N-1

Reinforcement options assessment (Security)	**Software**	Power-factory	CONVER-GENCE	PSD-BPA	Powerfactory	PSS/E	PSS/E, DSA	*Not available*	PSS/E, TARA	GE PSLF, PowerGem, TARA	PSS/E, POM, TSAT, TARA
	Timescale and sampling frequency	Winter peak snapshot - every 3 years	Snapshots; *Not available*	Snapshots; every typical year	Peak demand snapshots; every year	Peak/low demand and VRE output snapshots; every year	Peak and other demand snapshots; *Not available*	Peak congestion snapshots; every 10 years	Summer/Winter peak, Low load, natural gas pipeline contingen-cies	Summer peak, winter peak, winter off-peak spring off-peak 2, 5, 10 year + selected sensitivities	Summer & Winter peak day & night, Spring/Fall light load day& night Fall/Spring Shoulder Load
	Constraint	Voltage Thermal N-1/N-1-1/N-D Fault outage	Voltage Thermal N-1/N-1-1/N-D Fault outage	Voltage Thermal N-1/N-1-1/N-D Fault outage	Voltage Thermal N-1/N-1-1/N-D Fault outage	Voltage Thermal N-1/N-1-1/N-D Fault outage Frequency stability	Voltage Thermal N-1/N-1-1/N-D Fault outage	*Not available*	Voltage Thermal N-1, N-1-1, N-2 Fault	Voltage Thermal N-1, N-1-1, N-2 Fault Extreme Event	Voltage Thermal N-1, N-1-1, N-2 Fault

Reinforcement options assessment (Economy)	Software	BID3	ANTARES	SPER	Ameba	PLEXOS	*Not available*	*Not available*	PROMOD	ABB GridView	PROMOD
	Sampling frequency	Every 2-3 years	*Not available*	One in next 5-10 years and one in next 10-15 years	Every year	Every year	Every 5 years	Every 10 years	Every 3 to 4 years, 4 total.	Year 5 and 10	Every 5 years, 4 total
	Resolution and timescale	3-6h (up to 1 hour); whole year	Hourly; whole year	15 mins to hourly; typical day in each month	Few hours (8 blocks per day); typical weekday / weekend in each month	Daily energy limit to hourly power balance; whole year	Half hourly; whole year	Hourly; whole year	Hourly; whole year	Hourly; whole year	Hourly; whole year
	Operational model	Economic dispatch	Unit commitment	Economic dispatch	Economic dispatch	Simplified unit commitment	Economic dispatch	Economic dispatch	Unit commitment	Unit commitment	Unit commitment

	Constraints	Network constraints (thermal, voltage and fault outage) Lumped spinning reserves	Network constraints (thermal, voltage and fault outage) Lumped spinning reserves	Static network constraints Lumped spinning reserves	Network constraints (thermal, voltage and fault outage) Lumped spinning reserves System inertia constraint	Network constraints (thermal, voltage, fault outage, and system strenght) Lumped spinning reserves System inertia constraint	*Not available*	*Not available*	Network constraints (thermal, voltage and fault outage) Lumped spinning reserves System inertia constraint	Network constraints (thermal, voltage and fault outage) Lumped spinning reserves System inertia constraint	Network constraints (thermal, voltage and fault outage) Lumped spinning reserves System inertia constraint
	Reliability index[2]	LOLE	LOLE/LOLP/ EENS	EENS	EENS	EENS	*Not available*	*Not available*	*LOLP, ELCC*	*LOLE*	*ELCC, LOLE*
Decision making tools		LWWR	*Not available*	NPV maximi-sation	NPV maximi-sation	Weighted net market benefits and LWWR	*Not available*	*Not available*	*NPV*	*NPV*	Probabilistically weighted benefit to cost, Least Regret

[2] The reliability indexes considered here are the Loss of Load Expectation (LOLE), Loss of Load Probability (LOLP), Expected Energy not Supplied (EENS), and Effective Load Carrying Capability (ELCC)

2.1.3.1 Considerations on international best practices for TEP

Based on the review performed, key takeaways can be highlight as follows:

- Planning uncertainty is typically dealt with by scenario-based approaches.
- Most countries adopt a (very) limited number of scenarios in their planning methodologies, often building sensitivities around main scenario(s) rather than new, very different scenarios *per se*.
- In general, probability weights are rarely associated with the considered scenarios, possibly because the scenarios are only sensitivities. AEMO, MISO, and to some extent NGESO, are the exception to this rule. In the case of MISO, scenarios are weighted, and projects are selected based on the weighed benefit to cost ratio [59].
- Scenarios seem to be typically analysed independently and then planning options are chosen based on specific rules to make an integrated decision across several scenarios. National Grid and AEMO perform an integrated analysis across multiple scenarios via LWR/LWWR. MISO uses a least regret approach for its long-range transmission planning tranche [53]. CAISO also uses least regret to balance conflicting objectives [46].

AEMO, National Grid's and MISO seem to represent the state of the art of planning under uncertainty. This is to be considered in light of increasing operational complexity and uncertainty these system are incorporating in their methodologies. Similarly, inclusion of new operational characteristics and constraints, such as ones associated with low-inertia conditions, could be desirable.

2.2 Resilience in power system planning

Extreme events (usually weather-related) have resulted in substantial economic damages in the power grid. As weather events become more extreme, there is a growing need for a better understanding of their impact so as to reduce their negative effect on power system infrastructure. In this context, resilience in power systems has not only become a hot research topic but also an issue of extreme importance for countries worldwide, due to the need to better understand the events, their impacts on the operation of the grid and the solutions to reduce their negative effects on the operation of the system. This review does not aim to cover all the aspects associated with power system resilience (discussion about definition, operational planning to improve resilience and investment to increase power system resilience), but to focus on those challenges associated with investments to increase resilience.

Let’s start by defining power system resilience: the capacity of a power system to endure high impact and low probability (HILP) events (for instance, terrorist attacks, extreme weather events, natural disasters), recover from such disruptive events in a timely manner and, in the long run, adjust its operation strategies and available assets to mitigate the impacts of events of similar nature in the future [67], [68]. In this context, resilience can be defined as [69]: “The ability to withstand and reduce the magnitude and/or duration of disruptive events, which includes the capability to anticipate, absorb, adapt to, and/or rapidly recover from such an event”. CIGRE (C4.47 WG Members) has recently defined power system resilience as: “the ability of a power system to limit the extent, severity, and duration of system degradation following an extreme event”.

A framework to understand power system resilience is presented in [70] where also the key actions that can be conducted to improve network resilience are discussed. Power system resilience and its link to natural disasters is studied in [71], and several metrics to quantify resilience with consideration of fragility, survival and restoration in power systems are introduced in [72]. [73] extends the triangle to describe resilience and introduces the multiphase resilience trapezoid, also describing novel metrics to quantify resilience in each of the collapse-recovery phases. A framework to design and operate resilient networks with the consideration of risk aversion is presented in [74], which aims to decrease the exposure to extreme weather conditions and natural disasters. [75] proposes a resilience assessment methodology that considers four stages: threat characterisation, vulnerability assessment of system components, system response and system restoration. On the other hand, [76] introduces a resilience assessment method dividing this time in 3 steps: hardness before disasters, resistance during disasters and capacity of restoration after disasters. Besides the description of resilience events from a temporal perspective, [77] develops a fragility model of the transmission system that focuses on the impact of multiple regions on the probabilistic assessment of resilience. Resilience after earthquakes and mitigation strategies are studied in [78] with case study applications on the Chilean power system. [79] addresses the challenge of understanding resilience and designing mitigating strategies for HILP events using distributed energy resources.

Several operational and investment measures have been proposed to improve power system resilience [70], [74], [78], [80]–[85]. Power system planning considering resilience is discussed in several references, which include, but are not limited to, [82], [86], [87]. In particular, [86] proposes a transmission expansion problem using a multi-level optimisation model (describing the actions of an attacker and the strategies of a defender) to make investment decisions under terrorist threats. More relevant to this project is the study conducted in [82] which proposes a two-stage stochastic program and a solution algorithm to optimise investments that improve resilience in the context of seismic events. Another two-stage stochastic optimisation model is also proposed in [87], highlighting stochastic optimisation approaches as a promising tool for appropriate resilient decision making. [88] proposes a two-stage stochastic framework to identify network enhancements to improve resilience against earthquakes, using an optimisation and simulation solution approach. This approach enables capturing a very high level of detail and complexity in the simulation stage, including a comprehensive set of operational constraints and the sequential process of disconnection and reconnection of loads, which is key in evaluating the dynamics of resilience. [89] looks into the value of hardening existing infrastructure to improve resilience. This goes beyond the standard approach of looking at reinforcing the network with new/expanded assets to deal with low probability events. It highlights the difficulty behind this exercise as hardening of assets changes the outage probability associated to them. The methodology uses a scenario tree to model uncertainty, it characterises the threats using historical data, and assesses the vulnerability of components using fragility curves.

2.3 Integrated gas-hydrogen-power expansion planning

Many transmission system planners in countries with an abundance of renewable energy, including AEMO in Australia, are now considering the opportunities of large-scale green hydrogen in their scenarios. Depending on the evolution of hydrogen technology, its industry uptake, and the State and Federal Governments' support schemes and strategies, the impact on the planning of the electricity system can be substantial. AEMO's "Hydrogen Superpower" scenario in the 2022 integrated system plan (ISP) [90] predicts that the National Electricity Market (NEM) would need approximately 269 GW of wind and approximately 278 GW of solar - 34 times its current capacity of variable renewable energy (VRE) – to export green hydrogen, and support decarbonisation of heavy industry (e.g., green steel making), gas-fired generation (through hydrogen turbines), and end-use (by progressively switching households with gas connections to hydrogen-gas blend). This monumental scale of development will require the NEM to deliver eight times its current energy delivery by 2050.

Hydrogen can be produced from renewable energy through the power-to-gas (PtG) process [91], and transported and stored in liquid or compressed forms, or as a chemical compound such as ammonia [92]–[95]. This imminent advent of large-scale green hydrogen production raises the central question of which of the two options, transporting green hydrogen from distributed hydrogen producers co-located at the renewable energy zones (REZ), or transporting green electricity from REZ to a central hydrogen production hub, is the most cost-effective one across different distances, for different renewable energy portfolios, and subject to local availability of water and multi-vector storage options. The role of hydrogen as a way to transport renewable energy over long distances was identified in a 2018 report from IRENA [96], in light of the emissions reduction targets outline in the Paris Agreement. In this report, IRENA's roadmap for the energy transition towards low-carbon emissions is centred on key green hydrogen production technologies as the main drivers, particularly proton exchange membrane (PEM) electrolysers and fuel cells, which are approaching technical maturity and economies of scale. According to a recent study by CSIRO, the cost of PEM hydrogen electrolysers is projected to drop to nearly a third of its current costs by 2035 [97].

There are several studies on the design of hydrogen supply chains (HSC) in specific regions such as France [98] and Germany [99]. In particular, the work in [98] uses a multi-objective optimisation to design the HSC deployment scenario where three different objectives are considered to minimise total cost, CO_2 emissions, and safety risk. The work in [99] formulates the problem as a mixed-integer linear programming (MILP) problem that minimises the total cost of HSC, taking into account emission constraints. Moreover, a two-stage stochastic MILP is proposed in [100] for designing a liquid HSC while considering uncertainty in future hydrogen demand.

In order to overcome the fluctuations in hydrogen production from renewables, seasonal storage technologies can be incorporated into the HSC modelling [101], [102]. A multi-objective optimisation is also adopted in [103] to analyse a HSC network with the objectives of maximising the net present value and minimising greenhouse gas emissions. The work in [104] investigates the impact of co-deployment of hydrogen and CO_2 infrastructure on the transition of the heating sector from natural gas to hydrogen. In the supply chain, hydrogen transportation is the backbone that links production to utilisation, with tanker trucks, tube trailers, and hydrogen pipelines currently being the top three options [105]. Out of these three, hydrogen pipelines have been demonstrated to be the most cost-effective means for transporting large volumes of hydrogen over long distances [106], [107]. As an example, the work in [108] investigates the lowest cost of centralised hydrogen production and pipelines, whereas the pipeline network, including sizing and hydraulics, are studied by [109] and [110].

However, the above research is limited in scope as only the HSC is analysed, with no consideration of electricity infrastructure options. In the context of green hydrogen, including the electricity infrastructure as an option in the framework could unlock superior designs. This is especially true when considering the specific features associated with RES, and in particular when they are clustered in large-scale renewable energy hubs where wind and solar farms may be located far from the location of hydrogen utilisation. In this context, the key question arises as to whether it is better to locally generate hydrogen from renewable energy and transport it in pipelines, or transport electricity via transmission lines and then convert it to hydrogen at the location of the hydrogen export or demand, while also considering water availability, geographical constraints, and potential electricity and/or hydrogen storage options.

Such *integrated* planning of electricity and hydrogen networks has only been studied in recent years by a handful of researchers. A multi-objective MILP optimisation model is presented in [111] to design the integrated multi-vector energy networks for Great Britain (GB) in which energy can be transported as electrons by electricity transmission line or as molecules via gas pipelines, whereas [112] implements an MILP optimisation model to evaluate the optimal design of a hydrogen-based energy system in Germany in which only a pipeline transport option is considered. Moreover, the work proposed by [113] is used to design integrated wind-hydrogen-electricity networks to be used primarily for supplying the demand from the transport sector in GB. On the other hand, the model discussed in [112] is further extended in [114] by adding high-voltage direct current (HVDC) transmission lines to the energy transport options. However, these studies did not model the detailed dynamics of the gas system and therefore may be unable to capture the inherent storage capabilities of the pipelines (i.e., linepack). Furthermore, factors such as pipeline diameter and operating pressure are not incorporated into the mathematical model, thus, their influence on maximum energy transport capacity is not properly captured.

The study conducted in [115] designs and analyses a wind-powered hydrogen supply system considering both transmission connectivity between wind turbines and existing network and hydrogen transportation mode. However, the operation of each system, which is key in the presence of variable RES, is not captured in the model, thereby affecting its accuracy and optimality. Additionally, none of the above studies have modelled hydrogen production constraints due to regional water availability, which may be a key factor in real world applications. Furthermore, in [115], key physical parameters associated with the system capacity, e.g., diameter of a pipe or voltage level of an electricity line are not considered. Such capacity planning with assessments on different candidate capacity options is not analysed by [113] or [114] either.

The model developed by [116] incorporates both existing electricity networks and HSC to determine the optimal investment in electrolysers and hydrogen storage. However, there is no consideration of the (integrated) planning of electricity and hydrogen transmission infrastructure. On the other hand, the work in [117] compares the renewable energy transportation options including electricity transmission through HVDC and hydrogen transportation through pipelines. However, the inherent temporal variability of renewable energy production is not captured, which may subsequently alter the findings in the paper. Furthermore, the impacts of the system operation on the planning result are not considered either.

Recently, the importance of hydrogen production from renewable electricity in the transition to a net-zero energy system was discussed in the vision presented in the European hydrogen backbone (EHB) [118], [119], where a dedicated hydrogen pipeline network is proposed for connecting hydrogen supply and demand across many European countries. The majority of the proposed EHB pipeline network will be based on repurposing existing natural gas infrastructure, and it is anticipated to grow to a length of 39700 km by 2040. The EHB will be utilised to transport hydrogen produced from offshore wind farms and solar PV within Europe, as well as hydrogen imports from outside Europe. The work in [120] also investigates options for transporting RES across long distances. The study compares between two energy carrier options, namely, transporting RES as electrons via high-voltage alternating current (HVAC) lines or as molecules via hydrogen pipelines. In more detail, the renewable electricity transported through HVAC transmission line is used to produce green hydrogen at the demand location, whereas in the hydrogen pipeline option, green hydrogen is produced at the location of RES and then transported to the hydrogen demand point. However, the study in [120] only considers one RES location and one demand point and neither considers HVDC options nor models the storage capability of the linepack. The work in [121] also compares options of transporting hydrogen produced from offshore wind farms to onshore hydrogen production but the work disregards HVAC options, hydrogen storage, and does not consider the effect of the linepack in capturing the variability of the RES.

An insight into the anticipated hydrogen ecosystem development is given by [122], which states that scaling up hydrogen production in combination with proper regulatory frameworks could lead to a rapid decline in renewable hydrogen cost. This reduction in cost can be attributed to the anticipated drop in the cost of renewable generation. However, [122] also identifies that the drop in renewable cost is not enough to achieve low-cost clean hydrogen since the scaling of value chain of electrolysis is also a defining factor. Furthermore, it is widely believed that a cost-efficient hydrogen transmission and distribution infrastructure is key to unlocking large-scale hydrogen applications. Nonetheless, there is no straightforward solution for determining the optimal hydrogen transport option since it depends on many factors such as distance, terrain, and end-use application. Nonetheless, it is possible to achieve very low hydrogen transport costs for short and medium range distances if the existing pipeline networks were retrofitted to accommodate hydrogen. However, this in turn depends on the availability of an existing pipeline network that is suitable for retrofitting, as well as a higher rate of pipeline utilisation. Alternatively, in scenarios of low or fluctuating hydrogen demand, transporting hydrogen in trucks, in liquid or gaseous form, is more attractive. Over very long distances and international transport, transporting hydrogen at scale in new or retrofitted subsea pipelines may provide a cheaper option than shipping. Alternatively, if pipelines are not available, transporting hydrogen in liquid form or in chemical compounds is another viable option. An overview of hydrogen transportation costs is given Table 2.4, where different transport options are analysed for different distance ranges [122]. Note that the costs of ammonia and liquid organic hydrogen carriers (LOHC) include reconversion to hydrogen.

Table 2.4: H_2 transportation cost ($/kg) using different options in [122]

		Distance range (km)				
		0–50	51–100	101–500	>1000	>5000
Pipeline	Retrofitted	<0.1	<0.1	<0.1	0.1–1	N/A
	New	<0.1	<0.1	0.1–1	0.1–1	N/A
Shipping	Liquid H_2	N/A	N/A	N/A	1–2	1–2, >2
	Ammonia	N/A	N/A	N/A	1–2	1–2, >2
Trucking	LOHC	N/A	N/A	N/A	1–2	1–2, >2
	Liquid H_2	1–2	0.1–2	1–2	N/A	N/A
	Gaseous H_2	0.1–1	0.1–1	1–2	N/A	N/A

A recent study in [123] analyses different routes for shipping transportation of hydrogen and concludes that ammonia ($0.56/kg-$H_2$) and methanol ($0.68/ kg-H_2) are the least expensive hydrogen derivatives to transport, followed by liquified natural gas ($1.07/ kg-$H_2$), liquid organic hydrogen carriers ($1.37/ kg-$H_2$) and liquid hydrogen ($2.09/ kg-H_2). The authors in [123] acknowledge that cost profiles, demand factors, end uses, and economics are all expected to change rapidly in the coming years, which is why they developed an open-source

(Excel-based) tool to enable users to include a wide array of relevant costs for any shipping route globally, with the ability to update costs as the industry develops.

In summary, a systematic analysis of the fundamental drivers affecting infrastructure planning decisions across the two energy vectors and sets of technology has not been discussed in any work so far. In particular, the literature discussed above is either limited in scope to HSC without considering electricity infrastructure options or limited in the variety of considered infrastructure technologies. Other relevant works also ignore essential aspects such as voltage levels, pipeline diameters, pressure drops, linepack, and water availability, which can profoundly impact the optimal infrastructure design. To the best of our knowledge, [124] is the only work that incorporates essential nonlinearities such as voltage drops due to losses in HVAC and high-voltage direct current (HVDC) transmission lines, losses in HVDC converter stations, reactive power flow, pressure drops in pipelines, and linepack, all of which play an important role in determining the optimal infrastructure investment decision.

2.3.1 Comparison of transport options in the literature

Surprisingly, a *direct* comparison of the cost of energy transmission by electricity and by other types of energy carriers is addressed by only a handful of existing literature. In 2018, the work in [125] directly compared the relative costs of transporting electrical and chemical energy and determined that the costs of transporting electricity are substantially higher than the cost of transporting hydrogen. The same general trends are echoed in a recent work in [126], albeit with different estimates of the costs of individual energy carriers. This difference is due to the different assumptions in the underlying infrastructure options such as fluid velocity at minimum pressure (m/s) and capital costs ($/km), as well as the different assumptions and methods underlying the computation of capital costs. In more detail, [126] includes taxes and financial interest whereas [125] uses a simple capital recovery method in which the capital cost is levelised over the total amount of energy transported through the energy transportation option over the specified number of years. A summary comparison between the findings in [125] and [126] is shown in Table 2.5.

Table 2.5: Comparison of the results in [125] *with the ones in* [126] *for 1000 miles (1609.34 km)*[3]

	H_2 pipeline (900mm)		Electricity (HVDC)	
	[125]	[126]	[125]	[126]
Maximum pressure/voltage (MPa,kV)	10	10	500	500
Fluid velocity at minimum pressure (m/s)	15	18.6	NA	NA
Capital cost ($M/km)	1.99	0.87	1.43	2.42
Capital cost ($/MW-km)	210.1	103.1	480.2	933.3
Total cost ($/MWh-1609km)	4.0	5.0	4.4	41.5

[3] The total costs is the amortized cost in $/MWh per 1609km which combines the total of the operating costs and the amortized capital construction cost of a new line.

The differences in H_2 pipeline costs between [125] and [126] are less pronounced than the NG pipeline costs. This is mainly due to a smaller change in H_2 flow velocity between compression stations. The estimate cost for H_2 pipelines in [126] is slightly lower than of a NG pipeline. This lower cost is a result of using less compressor stations for H_2 pipelines (9 compressor stations per 1609 km) compared to NG pipelines (11 compressor stations per 1609 km). Additionally, since H_2 transmission is associated with a smaller pressure drop compared to natural gas transmission for the same distance, the volumetric flow rate is higher in H_2 pipelines than in natural gas pipelines. This explains why the estimate of the transport capital cost of H_2 in [126] is only *marginally* higher than that of natural gas.

The most notable difference between the findings in [125] and [126] is in the estimation of HVDC transport costs. In particular, the capital cost ($M/km) estimates in [126] are 70% higher than those in [125]. This is mainly because [126] considers the cost of converter stations at both the sending and receiving ends of the HVDC line, whereas [125] does not. In addition, despite the same HVDC link capacity being used in [125] and [126], the $/MW-km cost estimates in [126] are 2x larger than those [125]. This is mainly due to transmission losses which are captured in [126] but not in [125]. The above factors, compounded by the differences in the capital cost amortisation methods, translate to estimates of HVDC transport costs that are almost 10x larger in [126] than in [125].

In summary, the differences in the amortised and capital cost estimates between [125] and [126] stem from a combination of the following factors: (i) different methodologies for computing the volumetric flow of the compressible gases in the pipelines, (ii) accounting for losses in the HVDC lines, and (iii) the different capital cost amortisation methodologies. A more detailed summary of the comparison between the electricity (HVDC) and H_2 pipeline transmission infrastructure costs in the analysis of [126] is summarised in Table 2.6.

Table 2.6: Cost estimates of electricity (HVDC) and H_2 pipeline transmission infrastructure costs in the analysis of [126]

	H_2 pipeline (900mm)	Electricity (HVDC)
Total flow (kg/s, Amps)	69.54	6000
Delivered power (MW_{LHV}, MW)	8360	2656
Capital cost ($M/km)	0.9	2.4
Power loss in transmission	1.94%	12.9%
Capital cost ($/MW-km)	103.1	933.3
Amortised cost ($/MWh-1609km)	5	41.5

It is worth noting that in both [125] and [126] the utilisation factor of all the transport options is assumed to be 100%, which entails that the given transmission method is assumed to be used continuously at nominal design capacity.

HVAC transmission option is not included in Table 2.5 as it was found in [126] to be substantially higher than the cost of HVDC transmission. Nonetheless, recent work in [120] compares HVAC transmission lines to H_2 pipelines as two infrastructure options to transport

4000MW renewable energy in west Texas over *400 miles* (644km) to an H_2 demand point in east Texas. In those two options, HVAC transmission lines transport renewable energy as electrons, which is then used to produce H_2 at the demand point, whereas H_2 can be produced at the location of renewable energy and then transported via an H_2 pipeline to the demand point. In particular, the considered HVAC infrastructure consists of 5 double circuit 345 kV with 800 MW total capacity each. The reason behind choosing 345kV AC lines is that the majority of high-voltage transmission lines in Texas are 345 kV AC lines. As for the H_2 pipeline infrastructure, a 36-inch diameter (900 mm) is used with an operating pressure of 600 psi (41 bar). Under these parameters, the pipeline can transmit about 2.1M kg/day of hydrogen (equivalent to 3450 MW at an energy density of 141.7 MJ/kg, equivalently 12.78 MJ/m^3). The results of the comparison are summarised in Table 2.7.

Table 2.7: Cost estimates for a project lifespan of 20 years at 6% discount rate [120]

	H_2 pipeline (900mm)	Electricity (HVAC)
Maximum pressure/voltage (MPa,kV)	4.1	345
# of pipelines/HVAC lines	1	5
Total cost for 644km ($M)	1200	4000
Capital cost ($M/km)	1.86	6.21
Capital cost ($/MW-km)	466	1553
Total cost ($/kg-644km)	0.14	0.46
Total cost ($/MWh-644km)	**3.47**	**11.62**

The cost estimates in Table 2.7 do not include the cost of inverters, transformers (and reactive power support), and compressors, which explains the large differences between the findings in [120] and [126] in Table 2.5.

The scope of the works in [125], [126], and [120] is limited to the study of the cost of long-distance energy transmission by electricity, gaseous, and liquid carriers under a set of consistent technical and financial assumptions, as shown in Figure 2.1. In other words, [125], [126], and [120] neither consider capacity factors of the renewable energy sources nor the impact of electrolysers on the overall cost and transport efficiency. This type of analysis was recently conducted in [117], whose scope is also shown in Figure 2.1.

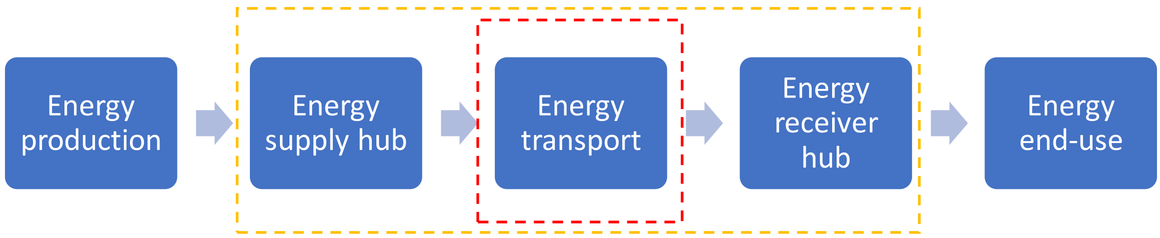


Figure 2.1: Scope of the existing works in [125], [126], *and* [120] *delineated by the dashed red rectangle. The scope of the work in* [117] *is delineated by the dashed orange rectangle.*

In more detail, [117] compares the levelised cost of energy (LCOE) of an H_2 pipeline and an HVDC link for a hydrogen supply chain scenario with 1000 MW of renewable power with a capacity factor of 32.7% over a distance of 4000km, and the main findings are shown in Table 2.8. The key assumptions behind the estimates in Table 2.8 are shown in Table 2.9. It can be seen from Table 2.8 that the LCOE estimate of the H_2 pipeline is about 15% higher than that of the HVDC line in this specific scenario (according to [117]). Also, the LCOE of both the H_2 pipeline and an HVDC link are around 4x larger than the LCOE of renewable energy (78.67 $/MWh from Table 2.9).

Table 2.8: LCOE of an H_2 pipeline and an HVDC link for a hydrogen supply chain scenario with 1000 MW of renewable power with a capacity factor of 32.7% over a distance of 4000km (Figure 2 in [117]*).*

	H_2 pipeline	Electricity (HVDC)
Pipeline/Cable ($/kg/4000km)	2.13	1.41
Electricity ($/kg/4000km)	4.24	5.72
O&M ($/kg/4000km)	2.28	0.04
Electrolyzer ($/kg/4000km)	1.05	1.05
Electrolyzer O&M ($/kg/4000km)	1.69	1.69
Total ($/kg/4000km)	11.39	9.9
Total ($/MWh/4000km)	**341.7**	**297**

Table 2.9: Main assumptions behind the estimates in Table 2.10 (Table 1 in [117]*).*

	H_2 pipeline	Electricity (HVDC)
Transmission capacity (MW)	1000	1000
Electrolyzer capital ($/kW)	1500	1500
Cable/Pipeline normalised Cost (M$/km)	0.34	0.34
O&M (%)	4.0%	0.1%
Renewable electricity ($/MWh)	78.67	78.67
Electrolysis efficiency	62.0%	62.0%
Lifespan	40 years	40 years
Capacity factor	32.7%	32.7%
Capital interest	8.0%	8.0%
Capital recovery factor (CRF)	14.9%	14.9%
Capital payback	10 years	10 years
Transmission efficiency	99.8%	86.0%
Transmission distance (km)	4000	4000

A major caveat regarding the estimates in [117] (Table 2.8) is that they were obtained from a predominantly *parametric* analysis that does not provide a detailed insight into the individual capital costs of associated converter and compressor stations. The exact diameter of the H_2 pipeline is not provided either. Only the carrying capacity of the pipeline in MW is provided.

3 Flexible expansion plan based on multi-stage stochastic planning

This section focuses on describing three fundamental aspects of the work conducted in this project, namely a brief description of the theoretical modelling of stochastic expansion planning, the data inputs used to describe the case study applications, and the results obtained for the reference case study application on top of which the remaining sections of the report are built.

3.1 Description of the stochastic planning model

The planning of the system's expansion presents a challenge that demands careful consideration of operational details to evaluate investment options while facing the complexities associated with expanding power systems under uncertain conditions. This work initially focuses on solving the problem of minimising expected cost, to later modify the objective of the problem to assess planning risk.

In the context of stochastic planning the uncertain parameters (e.g., load, renewable energy capacity, unit decommission, investment and operation costs) in the expansion model are depicted through a scenario tree. This tree captures the variables' uncertainty while maintaining the system's relevant interactions. The tree's nodes are organised into epochs, such as different years in the planning period, as illustrated in Figure 3.1. The example shows three scenarios with nodes covering the operation from start to finish of the horizon (Scenario 1: N1-N2-N4, Scenario 2: N1-N2-N5, and Scenario 3: N1-N3-N6).

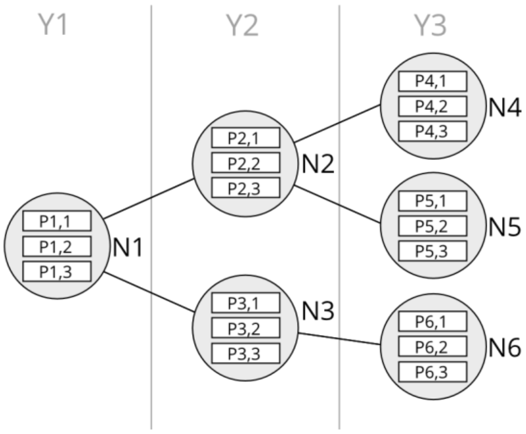


Figure 3.1. Scenario tree representing three yearly stages through six nodes, each of them containing three representative weeks. (PX-Y means period Y representing operation in node X)

Each node in the tree depicts the operation and investment for a specific year where the different uncertain variables have been assigned a value. For instance, node 2 and node 3 may differ in the amount of expected demand and renewable energy capacity installed in year 2, Y2. The two paths followed between nodes 1, nodes 2 and 3 represent the branching in future uncertainty (stochastic component of the model), which are usually modelled though a likelihood of each specific path to occur. The likelihood of each transition is expressed though a probability, and each set of paths stemming from a specific node must have a total probability of 1. If the paths between node 1 and node 2, and node 1 and node 3 are consider as likely to occur, then each of them will have a probability of 0.5. The probability of the transition between node 3 and node 6 is 1, as there is only *one future* expected to happen from node 3 onwards.

The system's operation is modelled through a set of independent representative days, weeks, or months, which are assumed to be independent. For instance, in Figure 3.1 the operation of each node is represented through 3 typical periods, which are labelled PX,Y, where X is the node number and Y is the period number. To clarify this even further, this means that the operation in node 1 will be represented by 3 weeks (could be days or months) of operation, that are selected from the 52 weeks in the year under analysis for that node. The 3 weeks could correspond to one week with the highest demand, one week with the lowest demand, and the one with average conditions. These are to be determined through a clustering or inspection strategy aiming to find the right conditions to value the investment options under consideration. Each of the representative periods can have a different weight throughout the year. In this study, the operation is represented through representative weeks using hourly steps, which represent a good trade-off between modelling complexity and a long-enough period to determine the value of storage technologies, as well as thermal units' technical constraints. Investment decisions for new assets are made at each node of the tree (which in this study covers a horizon of 20 years), considering models for each system element, which will be discussed in later sections.

The stochastic tree can be expressed as a single optimisation problem, known as the deterministic equivalent problem. For expansion planning case studies up to a certain size, where the tree size and operation representation are not overly large, the associated problem can be solved using available mixed-integer linear programming solvers (e.g., Gurobi), assuming the nonlinear parts of the problem would have been suitably linearised. This is what is done in this project, given that the essential value is in the methodological aspects of the different approaches being considered. For larger problems, caused by various stochastic parameters (e.g., number of scenarios, number of decision variables/investment options, etc.), detailed operation modelling, etc., decomposition algorithms might be needed in case the monolithic approach were to become infeasible due to the high memory demand and slow convergence of the branch-and-cut algorithm used to solve mixed-integer linear programs[4].

[4] Computational developments associated with the modelling are part of ongoing and future work.

3.1.1 Expansion planning problem

This section describes the main components of the underlying mathematical problem that describes the expansion planning problem under uncertainty. First, Figure 3.2 depicts the general structure of the planning model. The optimisation problem aims to minimise the total expected costs associated to the investment and operation decision made in each node of the scenario tree. The operation component of the total costs also includes the cost of not serving energy to the customers at any given period, which in the context of this study is valued at the current market price cap for the National Electricity Market.

OBJECTIVE FUNCTION (MIN)

costs

Sum of expected (inv + op) costs
for the nodes of the scenario tree

subject to CONSTRAINTS

INVESTMENT

POWER SYSTEM OPERATION

UNIT COMMITMENT

Figure 3.2. General structure of the stochastic planning problem

This objective function is subject to a set of constraints that includes:

- Investment constraints: these include the so-called non-anticipativity constraints, which guarantee that an investment made at a certain node in the scenario tree will be present in the subsequent nodes connected to said node. These constraints also include the potential rules of investment across the portfolio of options, for instance, investment options that are mutually exclusive, investment options that must follow another investment option, or investment options that must be built simultaneously.
- Power system constraints: these correspond to all the constraints associated to power system operation, including energy balances, reserve provision, power flow, transmission limits, etc.
- Unit-commitment constraints: the operation of conventional units in the system is bound by their technical characteristics, for instance, ramping limits, minimum stable generation, start-up times, etc.

The structure of the problem presented in Figure 3.2 can be translated into a comprehensive mathematical problem, although here we do not introduce those details. For further details on the modelling of power system operation, see [127]

The objective function of the stochastic investment problems adds up all the investment and operation costs of the set of nodes (and associated representative weeks) in the scenario tree. Note that the operation of each representative week can be multiplied by a factor to reflect the weight of that representative week in the operation of the year associated with the node that contains it. These costs are discounted from the year associated to each node to a reference year using a given rate of return. Also, since the approach considers expected cost minimisation, each node is weighted by its probability of occurrence.

The different studies on expansion planning presented in this report use the information presented in the 2022 Integrated System Plan (ISP) [1]. Even though the expansion methodology presented in this project is fundamentally different from the ISP methodology, it is relevant to briefly describe the ISP approach to understand the input data of the study. Then, the input data used in the case study applications is introduced, along with the description of the representation of the future and uncertainty.

3.2 Integrated System Plan 2022 methodology

AEMO's ISP process covers a decision horizon of 20 years and includes the effect of distributed energy resources (DER), virtual power plant (VPP), grid-scale generation, energy storage systems (ESS), high voltage transmission, the gas system, hydro resources, and the electrification of transport. The ISP2022 also considers the effects of the emerging global hydrogen economy in Australia.

The ISP addresses the power system needs for reliability, security, public policy objectives and their supporting system standards. The transmission expansion decisions necessary to leverage the transition from a coal-fired generation dominated system to a low-carbon, low-inertia system dominated by variable renewable energy sources (VRES) and DER are made using a least-cost and least-regret approach.

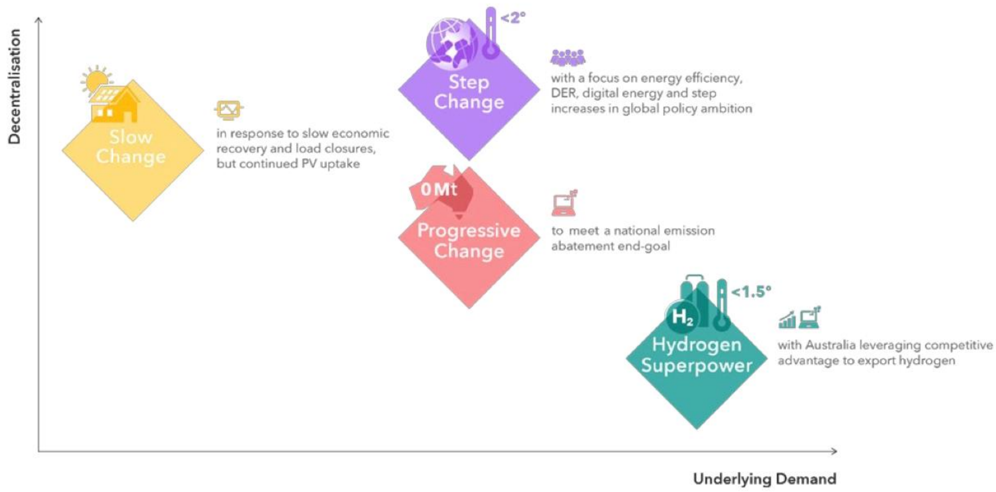


Figure 3.3. ISP scenarios (Source [1]*).*

In order to determine the optimal transition path for the system, the ISP models the future through a set of scenarios (see Figure 3.3) that are characterised by varying load levels (LOAD) and supply profiles (VRES and DER), energy storage parameters and investment costs, the behaviour of the gas and electricity markets, etc. Figure 3.3 allows to understand how each scenario balances the decentralisation and the underlying operational demand seen by the transmission network in each scenario. On top of the four scenarios, the methodology considers additional sensitivities on future scenarios, including considering higher discount rates, lower gas prices, stronger electrification, etc.

The methodology aims to find the least cost development path for each scenario and sensitivities separately. Each deterministic least cost development path is determined using a generation and transmission expansion model resulting in hourly dispatch outcomes that are then tested for security criteria (fault levels, dynamics, voltage compliance, etc.) using electromagnetic transient analysis software. Then, using those results, it determines the least-regret development path across all scenarios, as described in Figure 3.4.

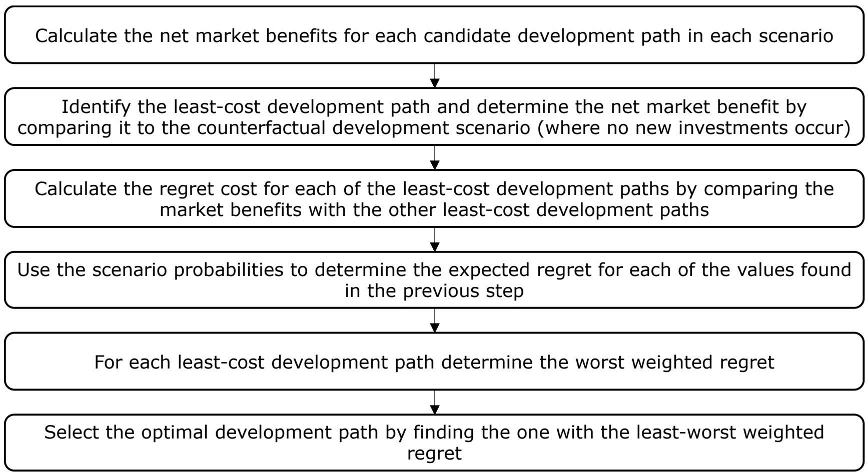
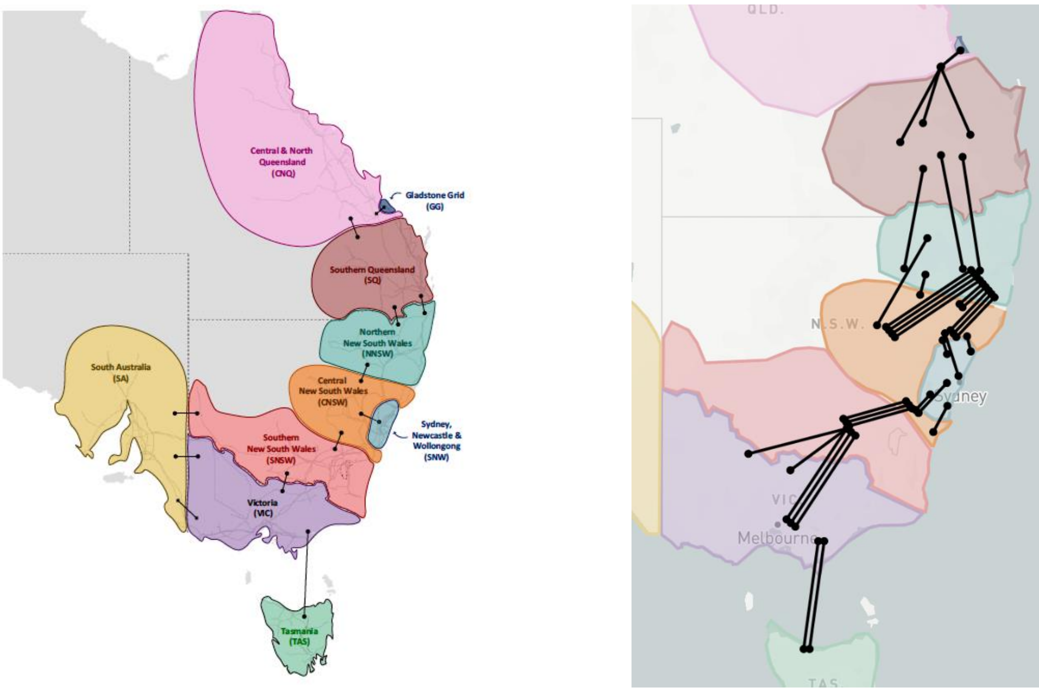


Figure 3.4. Steps for the calculation of the least-regret path in the ISP2022.

As seen in steps described in Figure 3.4, after calculating the weighted net market benefits for each scenario a least-worst weighted regret (LWWR) approach (originally proposed in [128]) is used by AEMO for ranking candidate development paths in the optimal development path determination process. The LWWR approach identifies the path with the least regret from under- or over-investment considering uncertainties across scenarios. The LWWR approach takes scenario weights into account to reduce the impact of unlikely scenarios, as opposed to the standard LWR approach which is equivalent to considering equal scenario weights [128]. AEMO calculates regrets by determining the largest net market benefit for each scenario and comparing it to other candidate development paths for the system. The greater the deviation from the least-cost development path, the greater the regret.

All the information necessary to run the steps described above is available to the public, including the partial results of each step of the methodology. This work uses the information associated with the generation investment plan and retirements in each scenario, the demand data (which already considers the effect of electric vehicles and behind-the-meter storage), transmission and storage investment options and associated capital costs. The following section describes the details about the input data describing each of the scenarios.



a) Subregions in ISP 2022　　*b) Transmission candidate investment options*

Figure 3.5. NEM system regions and transmission candidate investment options modelled in the ISP 2022

3.3 Input data

The system under consideration corresponds to the Australian NEM as defined in the input assumptions database associated to Integrated System Plan (ISP) 2022 [1]. Some of the data used in this work is obtained from the results associated to the optimal development path found in the ISP2022, which corresponds to the candidate development path 12. Figure 3.5a depicts the 10 subregions under consideration in the ISP for the expansion planning exercise. Figure 3.5b highlights the candidate lines (black segments) considered in the ISP 2022 (the picture excludes commercial solutions also considered in the ISP 2022).

3.3.1 Initial system and trends

The existing generating units are grouped into clusters of equivalent (or close to equivalent) generators per technology per subregion to reduce computational effort while maintaining very good operational resolution [129]. Table 3.1 presents the techno-economic parameters of the synchronous units in year 2022.

- Central & North Queensland (CNQ) is represented through a cluster of coal units, two cluster of gas- fired units, a cluster of Diesel units and one group of hydro units.
- Gladstone Grid's (GG) synchronous units are represented through a coal-fired cluster and a gas unit.
- Southern Queensland (SQ) is represented through four coal clusters and three gas-fired clusters

- North New South Wales (NNSW) only has renewable energy technologies operating in it.
- Central New South Wales (CNSW) considers one cluster of coal units and a different cluster to represent the Diesel capacity available in the subregion.
- Sydney, Newcastle & Wollongong (SNW) synchronous fleet is represented through two clusters of open-cycle and combined cycle gas units.
- Southern New South Wales (SNSW) consists of a cluster of open-cycle gas turbines and one cluster of hydro units.
- Victoria (VIC) is modelled using three clusters: one cluster of brown coal units and two clusters of gas turbines.
- South Australia's (SA) generation fleet is modelled using two clusters of open-cycle gas-fired units, one cluster of combined cycle gas turbines and two clusters of Diesel units.
- Tasmania (TAS) is represented using three clusters of gas-fired units and one cluster of hydro resources.

Figure 3.7 shows the evolution of coal units' retirements by scenario. The clusters including coal units are modified depending on the specific changes in the generation fleet described in the optimal development path found in the ISP 2022.

Table 3.1. Referential techno-economic parameters of units available in 2022 (Source [1]

Technology	Coal	Hydro	OCGT	CCGT
Number of units	48	110	93	10
Variable cost [$/MWh]	12-42	7.3	95-490	65-79
Start-up costs [k$]	46-93		0.4-6.5	12-46
Rated Power [MW]	354-744	25-127	33-500	180-644
Forced outage rate [pu]	0.77-0.87	0.975	0.88-0.98	0.98
Minimum Stable Generation [MW]	141-300	5-25	8-165	44-190
Ramp rate [MW/min]	3.5-6		3	2-10
Inertia constant [s]	4	2.5	4	4
Min up time[h]	8-16			4-6

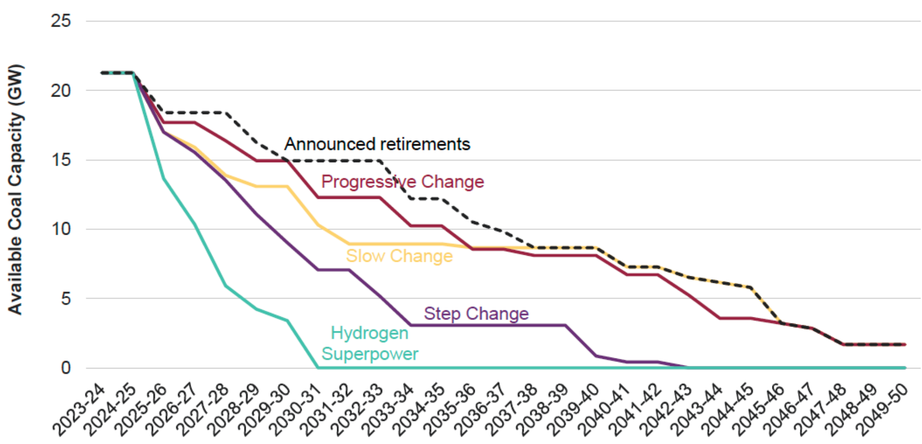


Figure 3.6. Coal fired capacity retirements by scenario (Source [1]*).*

Non-synchronous generation is split into large scale wind, large scale solar PV and rooftop solar PV, represented each as a single unit in each state. The capacity of these units changes in the different nodes of the tree to reflect the growth in installed capacity. In order to have access to the most precise information about demand in the system (e.g., to account for its natural response after frequency changes for the sake of calculating reserve requirements), rooftop solar PV is modelled as a separate unit hence avoiding the need to subtract it from the gross demand for each state. The installed capacity for the different generation technologies for scenario *Step Change* (considered the most likely scenario) is depicted in Figure 3.7.

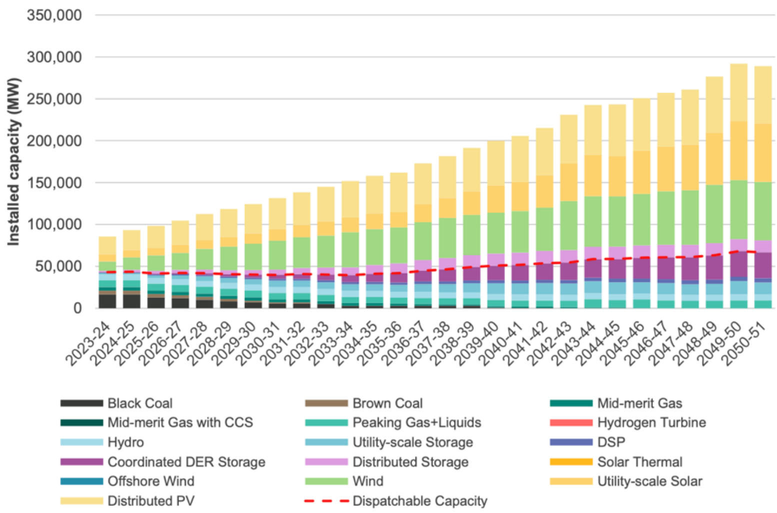


Figure 3.7. Installed capacity by technology by scenario (Source [1]*).*

The transmission system considers 11 existing links between the different subregions, whose forward and reverse maximum active power transfers are specified in Table 3.2. The table also includes project EnergyConnect between SA and SNSW, which although under development, it is considered to start operations in 2026. Following the ISP's approach, Kirchoff's voltage law is not modelled, which in general is not an issue, as the network is mainly radial, with the exception of the loop seen between SA, NSW and VIC. This approximation might affect the valuation of investment options across the system, but in particular those connecting NSW and VIC. .

AEMO models four different types of storage systems: behind-the-meter storage, coordinated distributed storage, and both battery energy storage systems (BESS) and pumped-hydro storage systems (PSS) with different charging depths. The effect of behind-the-meter storage is included in the demand profiles. Controllable distributed storage is handled as a virtual power plant (VPP) equivalent generator with dispatchable capacity to only perform arbitrage in the system (no provision of frequency response).

Table 3.2. Characteristics of existing and expected transmission lines

Transmission line	Region A	Region B	Transfer limit [MW]	
			A to B	B to A
CNQ->GG	CNQ	GG	1050	1100
SQ->CNQ	SQ	CNQ	1000	2100
QNI	NNSW	SQ	745	1170
Terranora	NNSW	SQ	50	200
CNSW->NNSW	CNSW	NNSW	910	1025
CNSW->SNW	CNSW	SNW	7625	6125
SNSW->CNSW	SNSW	CNSW	2950	2590
VNI	VIC	SNSW	1000	400
Heywood	VIC	SA	650	650
Murraylink	VIC	SA	220	200
Basslink	TAS	VIC	478	478
Project EnergyConnect	SNSW	SA	800	800

The ISP organises utility-scale storage in three categories: shallow, medium, and deep. Shallow storage considers a storage capacity of less than 4 hours, medium storage units cover the range between 4 and 12 hours, and deep storage considers units with more than 12 hours of storage capacity. Current storage levels by type include 570 MW and 100 MW of medium and deep storage in Queensland, respectively. NSW has 50 MW of shallow storage, 80 MW of medium and 150 MW of deep storage. Shallow storage in VIC is currently 120 MW and in SA 470 MW. In general, for existing and new BESS, the round-trip efficiency is considered 82%, while for existing pumped-storage hydro the round-trip efficiency is 72%. In Figure 3.7 it is possible to see the optimal storage capacity (dispatchable and behind-the-meter) determined by AEMO for the step scenario.

In our stochastic plan modelling exercise, the optimal dispatchable storage capacity identified by AEMO is included in the description of the system as an input. Additionally, some case study applications also consider the possibility to invest in additional storage in order to observe the effects on the flexible plan of allowing the model to choose investment options other than transmission lines.

From the point of view of frequency security, the model allocates primary and secondary frequency response to comply with a settling frequency (quasi-steady state frequency, QSSF) value of of 49.5 Hz in low-frequency events; secondary frequency response is allocated to bring frequency back inside the frequency dead-band (above 49.85 Hz). For simplicity, although it is possible to enable such constraints in the modelling [130], no frequency extrema constraints or rate of change of frequency (ROCOF) constraints were used in this study.

Demand in the system is obtained from the database associated with [1]. The information is used to run the model considering hourly periods. In this case study application, a 10%

probability of exceedance (POE)[5] demand scenario is used, and, as pointed out before, it includes the effect of behind-the-meter storage in each scenario.

3.3.2 Investment options

Investment options include transmission lines (and in some cases, BESS). All investment related cash flows manipulations (annuities, discounting, etc.) are calculated using a capital cost of 10%.

The stochastic planning model has the capacity to model real transmission options[6], that is, the specific projects that are considered in the ISP and the relationships among projects. In this sense, the portfolio of options can be represented both considering *mutually exclusive* projects and *must follow* projects. The consideration behind mutually exclusive sets is that only one option can be built if this results in benefits for the overall expected cost minimisation objective of the problem. Must follow projects are represented as options that have to be in place in the system to build another option (simultaneous construction is also accepted). To focus on the transfer capacity requirements between boundaries, the new links are not subject to Kirchhoff's voltage law (transport model only), as aforementioned.

Table 3.3 presents the parameters for the different network reinforcement options. For the sake of simplicity, all reinforcement options consider a lifetime of 50 years and a lead time of 5 years (time elapsed between investment decision time and asset's initial operation time). The investment costs presented in Table 5.3 correspond to overnight capital costs, and it is assumed these costs do not change in the future. Some of the reinforcement options considered by AEMO are not used in the context of this study; they all correspond to non-network options, whose investment cost was not disclosed, and they are coloured grey in Table 3.3. Also, some transmission investment options have been slightly modified to fit the modelling of the mutually exclusive and must follow rules. However, these changes should not affect the outcome relative to the original database. The options that have been modified are: the pair CNSW-SNW Options 3a (replaces original option 3) and 3b (this option was added to the list), and the triad CNSW-NNSW Options 6, 6A and 6B. An approximated geographical representation of the transmission investment options is presented in Figure 3.8.

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[5] POE is the chance a maximum demand forecast will be surpassed. For example, a 50% POE maximum demand forecast is expected to be exceeded, on average, 5 years in 10.

[6] An alternative approach to these real transmission options that could be enabled in the modelling could be to determine the overall transmission capacity needed between regions. This corresponds to only introducing *one* reinforcement option between pairs of adjacent regions and then determine an overall transfer capacity reinforcement investment value based on the average capital costs presented in the ISP2022 for the reinforcement alternatives considered in that specific boundary. Such an approach would be much less computationally expensive and cold considered for high level, strategic initial studies.

Table 3.3. Investment options in transmission lines

Line	Line ID	Region A	Region B	Transfer limit (MW)		Investment Cost (M$/MW)
				A to B	B to A	
CNQ-GG Option 1	13	CNQ	GG	550	500	0.74
SQ-CNQ Option 1	14	SQ	CNQ	900	900	0.53
SQ-CNQ Option 2	15	SQ	CNQ	0	300	0.18
SQ-CNQ Option 3	16	SQ	CNQ	*Non-network option, info missing*		
CNQ-SQ Option 4	17	SQ	CNQ	1500	1500	1.08
NNSW–SQ Option 1	18	NNSW	SQ	910	1080	1.16
NNSW–SQ Option 2	19	NNSW	SQ	550	800	0.48
NNSW–SQ Option 3	20	NNSW	SQ	*Non-network option, info missing*		
NNSW–SQ Option 4	21	NNSW	SQ	1800	2000	1.56
CNSW-NNSW Option 1	22	CNSW	NNSW	2035	1660	1.76
CNSW-NNSW Option 2	23	CNSW	NNSW	710	535	2.72
CNSW-NNSW Option 3	24	CNSW	NNSW	585	470	2.39
CNSW-NNSW Option 4	25	CNSW	NNSW	710	535	2.67
CNSW-NNSW Option 5	26	CNSW	NNSW	585	470	0.87
CNSW-NNSW Option 6	27	CNSW	NNSW	2190	1800	0.77
CNSW-NNSW Option 6A	28	CNSW	NNSW	880	1270	0.18
CNSW-NNSW Option 6B	29	CNSW	NNSW	2750	2750	0.45
CNSW-NNSW Option 7	30	CNSW	NNSW	1470	1590	0.56
CNSW-NNSW Option 8	31	CNSW	NNSW	*Non-network option, info missing*		
CNSW-NNSW Option 9	32	CNSW	NNSW	1750	2000	1.06
CNSW-NNSW Option 10	33	CNSW	NNSW	1750	2000	1.15
CNSW-SNW Option 1	34	CNSW	SNW	5000	0	0.18
CNSW-SNW Option 2	35	CNSW	SNW	4500	0	0.50
CNSW-SNW Option 3a	36	CNSW	SNW	600	0	3.76
CNSW-SNW Option 3b	37	CNSW	SNW	1100	0	0.80
H-Newcastle	38	CNSW	SNW	5000	5000	0.31
H-Dapto	39	CNSW	SNW	5000	5000	0.24
SNSW-CNSW Option 1	40	SNSW	CNSW	2200	2200	1.51
SNSW-CNSW Option 2	41	SNSW	CNSW	2000	2000	0.48
SNSW-CNSW Option 3	42	SNSW	CNSW	2000	2000	1.02
VIC-SNSW Option 1 - VNI West	43	VIC	SNSW	1930	1800	1.40
VIC-SNSW Option 2 - VNI West	44	VIC	SNSW	1930	1800	1.52
VIC-SNSW Option 6A	45	VIC	SNSW	1930	1800	1.20
VIC-SNSW Option 6	46	VIC	SNSW	2000	1500	1.16
VIC-SNSW Option 7	47	VIC	SNSW	2000	2000	1.26
TAS-VIC Option 1	48	TAS	VIC	750	750	3.17
TAS-VIC Option 2	49	TAS	VIC	750	750	1.87

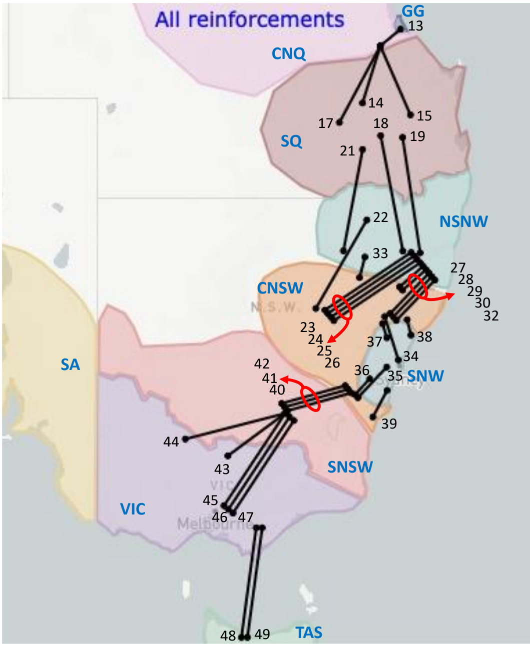


Figure 3.8. Geographical referential location for the transmission investment options highlighting line ids

In those cases where additional investment in energy storage systems is studied, to keep things relatively simple only BESS units with 4 hours storage capacity are considered (this duration value was selected to try to reflect the value of shallow and medium depth storage). Each subregion can expand BESS independently up to 20GW in blocks of 100MW, as depicted through blue dots in Figure 3.9 .

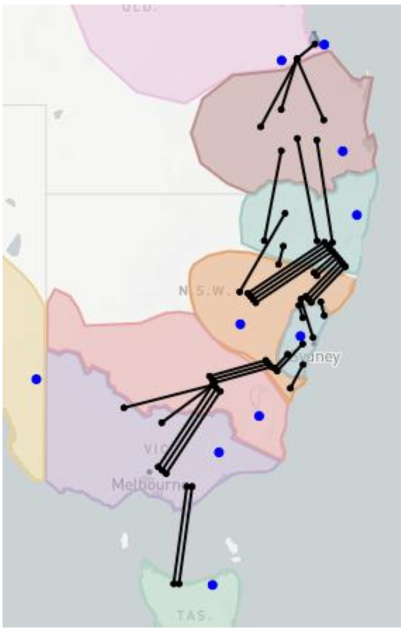


Figure 3.9. Candidate investment options when considering the co-investment of transmission (black) and BESS (blue)

This means that the model will explore multiples of 100MW batteries with 400MWh storage capacity each. The investment parameters for storage projects are presented in Table 3.4.

The lead time of storage is 0, which means that the decision to build storage and the availability of the device is assumed to happen simultaneously. All BESS in the system (existing and new) are assumed to be able to provide frequency response up to 70% of their capacity, in the form of primary frequency response (no fast frequency response consideration, as we are not constraining frequency extrema in these studies, although the model could allow that, as mentioned above). The investment costs for BESS reduce in time, and the change in investment costs depends on the scenario (see Table 3.5). All the details about these assumptions can be found in the input assumptions database associated with [1].

Table 3.4. Characteristics of storage investment options

Region	Tech	Charging capacity (MW)	Energy storage (MWh)	Life time (years)	Expansion modules
ALL	BESS	100	400	20	200

Table 3.5. Investment cost evolution for battery energy storage systems

Scenario	Region	Investment cost by year (M$/MW)			
		2022	2027	2032	2037
Slow Change Progressive Change	All	1.613	1.372	1.016	0.850
Step Change H_2 Superpower	All	1.377	0.912	0.705	0.630

The model includes the capability of making decisions on new generation fleet. However, in this study all generation-related decisions are copied from the optimal development path determined by AEMO.

3.3.3 Scenario modelling and investment decision architecture: scenario tree

The case study applications conducted in this study consider a complex representation of future uncertainty built based on the four scenarios considered by AEMO. As discussed in the literature [23], the more uncertainty is captured in the representation of the future, the more value can be identified for critical investment options.

Figure 3.10 shows the structure of the multi-stage modelling approach adopted here, which was built using the information provided by AEMO for each of the scenarios under consideration in the ISP 2022. However, the scenarios were rearranged, and new, “intermediate” scenarios created, in a way that the resulting scenario tree would more closely emulate potential "incremental" transitions across scenarios. Incremental here refers to "plausible” transitions to scenarios that have higher demand or decentralisation profiles: for instance, if the system is in the progressive change scenario, it can stay in that scenario or transit to the step or hydrogen superpower scenarios. It cannot, however, transit to the slow scenario. It should be noted that these assumptions are just one approach to model uncertainty; in general, the planner can design any future that may seem plausible and/or interesting to consider, in case through specific consultations, not too dissimilarly from how the original four scenarios were developed by AEMO.

Another relevant aspect behind the representation of uncertainty is to determine the probabilities of transition between subsequent nodes. In order to do so in this study, we use the probabilities (see Table 3.6) determined in the ISP process for each of the four scenarios under consideration.

Table 3.6. ISP 2022 scenario probabilities

Scenario	**Probability**
Slow Change	4%
Progressive Change	29%
Step Change	50%
H_2 Superpower	17%

The methodology to assign probabilities is as follows. The transition between years 2022 and 2027 is straightforward and the corresponding probability for each scenario is used. When the transition doesn't include the four scenarios (that is, when the paths stemming out of one node do not include the four scenarios), the probability of the scenarios that are not considered are added up to the transition that stays in the same scenario.

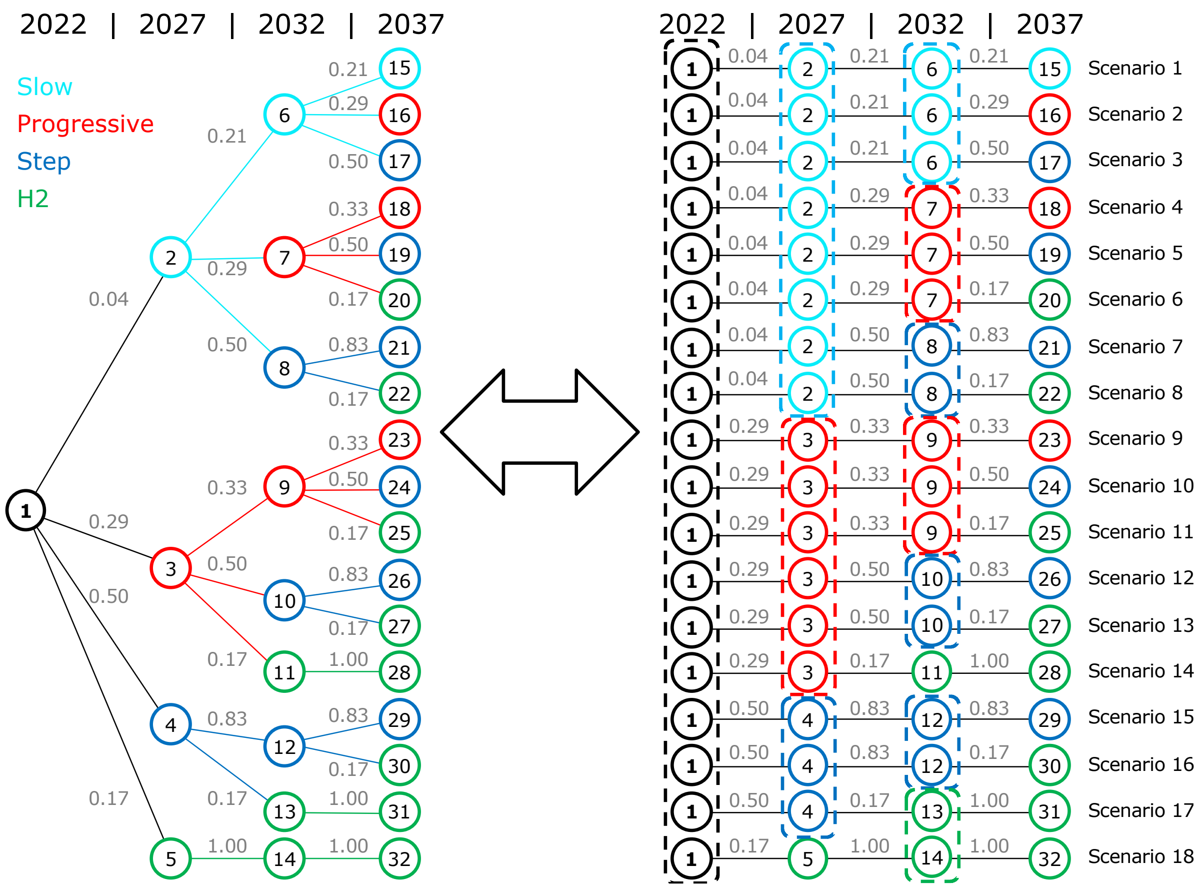


Figure 3.10. 32-node scenario tree, corresponding to 18 "path" scenarios, used in the studies

For instance, let's take node 2 (slow change in 2027); the possible transitions following the incremental approach are to stay in the slow scenario or to evolve to progressive or step change scenarios. Following the probability assignment methodology, both the progressive and step change transitions get their original probability as presented in Table 3.6. The slow transition gets the sum of the probabilities of all remaining scenarios, in this case the probability of the slow change (4%) and H_2 superpower scenarios (17%), resulting in a probability of 21%. This approach has the advantage of giving more relevance to the transition that stays in the same path as the current node. As with the structure of the scenario tree, the probability of the transitions is part of the design that the planner must conduct. The exact methodology to determine those probabilities is something that is again open for discussion, but the stochastic planning framework is flexible and supports any combination of probabilities as exogenous input data.

A note on terminology: the term ***scenario*** refers to one of the ***paths*** connecting the root node (2022) to any of the leaf nodes representing the conditions of the system for year 2037. The scenario tree presented on the left-hand side of Figure 3.10 contains 18 scenarios (which will be referred to as scenario X, where X corresponds to the number of the leaf nodes starting at 1 from the top of the tree), as shown in the right-hand side of the exhibit (the dashed boxes around nodes mean that the decisions made in the nodes contained in the boxes are the same, given the structure of the tree). It is interesting to highlight that the construction of the multi-stage tree used in this study contains, as a subset, all the scenarios used in the ISP 2022, that is, scenario 1 represents the slow change scenario, scenario 9 corresponds to the progressive change scenario, scenario 15 is the step change scenario, and scenario 18 corresponds to the H_2 superpower scenario. The nodes for each scenario, as well as the corresponding probability, are presented in Table 3.7.

Table 3.7. The 18 scenarios associated with the 32-node tree and corresponding scenario probabilities

Scenario ID	Probability	Node 2022	Node 2027	Node 2032	Node 2037	ISP Scenario
1	0.0018	1	2	6	15	SLOW
2	0.0024	1	2	6	16	-
3	0.0042	1	2	6	17	-
4	0.0038	1	2	7	18	-
5	0.0058	1	2	7	19	-
6	0.0020	1	2	7	20	-
7	0.0166	1	2	8	21	-
8	0.0034	1	2	8	22	-
9	0.0316	1	3	9	23	PROGRESSIVE
10	0.0479	1	3	9	24	-
11	0.0163	1	3	9	25	-
12	0.1204	1	3	10	26	-
13	0.0247	1	3	10	27	-
14	0.0493	1	3	11	28	-
15	0.3445	1	4	12	29	STEP
16	0.0706	1	4	12	30	-
17	0.0850	1	4	13	31	-
18	0.1700	1	5	14	32	H2

In this study, we use a decision-making architecture that makes decisions every five years, corresponding to the considered epochs represented in the tree, which is linked to the lead time used for the transmission investment options. This architecture is flexible and can potentially be different, thus changing the design of the scenario tree [23]. It is important to note that some decisions could be made annually for the initial years of the study, and others every 2, 5, 10 years for nodes representing future years far away from the present. This variation in decision-making frequency corresponds to different decision-making architectures and representations of the future, and it is considered part of the trade-off (as opposed to modelling all the years within a 20 to 30 year period) necessary to arrive at a representation that is tractable within the timeframes of this type of study. As a result, this flexible methodological aspect should be taken into consideration in future studies.

3.3.4 Operational data selection

Although off-the-shelf state-of-the-art MILP solvers can efficiently handle extremely large problems, the larger the problem, the slower the search process will be (and the larger the underlying computational infrastructure needs are). To help reducing the computation time, and in line with the methodological focus of this work, each year under analysis is represented by a subset of representative weeks (decisions are made on hourly steps, which results in 168 periods within each typical week) selected among the 52 available weeks[7].

For each of the years selected to sample the scenarios, the following steps were taken to identify the subset of weeks closest to represent the operation of the 52 weeks: first, select the year and split all the corresponding data series into 52 weeks. Then, 6 weeks are selected (as a comparison, in Figure 3.1 the problem was structured using three representative weeks) to represent the periods with maximum and average demand, for different levels of renewable energy availability within the year at both system and state levels. The number of weeks could be increased or modified depending on the requirements of the study and the computational resources available.

For the sake of simplicity, and to focus our efforts on the methodological developments and outcomes, many of the studies conducted in this work use only one week per node in the scenario tree to represent operation. This approach was used to reduce the computational burden of the problem to maximise the number of studies that we could run, so as to be able to provide the best insights possible (the exact investment decisions are not the most relevant insight; in contrast, the relative behaviour of investment decisions when comparing different one-week-based studies enable understanding the value of the different models studied in the project). For the detail about the operational weeks selected for each node in the 6-week representation approach, see Appendix A. For the 1-week representation we use the first representative week presented in Appendix A for each node.

3.3.5 Summary of databases and constraints

The following Table summarises the information used to feed the stochastic planning model. The table explicitly states the main assumption behind each dataset in case the information were not directly used from the assumptions database. The table references the optimal development path (ODP) determined by AEMO in the ISP 2022, which corresponds to the candidate development path number 12 (CDP12).

[7] In general, the selection of the input data is important to ensure adequate representation of the system's operation [137], which can have a substantial impact on the investment decisions derived from the long-term operation model.

Table 3.8. Dataset summary and considerations

DATASET	CONSIDERATIONS
Buses	Using subregional approach (10 buses)
Areas	States
Lines / Interconnectors	
Lines – Seasonal ratings	
Lines – Investment candidates	Must follow, mutual exclusivity considered
Storage (Shallow/Medium/Deep)	Based on ISP 2022 CDP12 (ODP)
Storage – Investment candidates	
Storage – VPP	
Demand	
Demand – Load time series	
Generators	Based on ISP 2022 CDP12 (ODP)
Generators – UC parameters	Using ISP 2020 parameters for coal
Generators – Variable costs	
Generators – Retirements	Based on ISP 2022 CDP12 (ODP)
Generators – Rooftop PV	
Generators – Large scale RES aggregation	Based on ISP 2022 CDP12 (ODP)

The constraints considered to model the operation of the power system and the frequency response considerations are summarised in Table 3.9.

Table 3.9. Constraints considered to model the operation of the system

Operation-related constraints
Line transfer limits
Minimum down time
Minimum up time
Minimum stable generation
Maximum rating
Ramps
Start-up costs

Frequency response-related constraints
Largest contingency constraints
Generation contingency
Primary frequency response up
Secondary reserve up
Quasi-steady state frequency

3.4 Case study application

In this section we present the results associated with the case study that is used as a reference in this report. It corresponds to the expected cost minimisation problem as described in Figure 3.2, for the 32-node scenario tree depicted in Figure 3.10, using six representative weeks of operation for each of the 32 nodes (resulting in 192 weeks to model operation). This instance will be labelled “ISP22_32N_6W” and it only considers decisions on new transmission investments.

Before presenting the results for this instance it is worth presenting a few facts about the underlying computational burden. All the results presented in this report correspond to solutions obtained for the monolithic problem (that is, no decomposition was used to solve this problem). A feasible solution is searched using the optimisation solver Gurobi 9.0.3 [131], until the MIP gap is below 1% (for further information about the definition of the MIP gap see

[132]). This is important because there is a space for flexibility when it comes to find the optimal solution, which needs to be kept in mind when interpreting some results (in a problem with an optimal expected cost close to $20 billion, a 1% tolerance translates into a potential space of $200 millions within which two solutions might be equivalent from an optimality point of view). The underlying model has total of over 21 million variables (2176 variables are integer, resulting from considering 34 transmission investment options in each of the 32 nodes of the tree, which include two decisions per investment option, namely, the decision to build and the decision to deploy the asset) and over 29 million constraints. Solving the instance ISP22_32N_6W takes up to 17.5 hours using 30 CPUs in the high-performance computer *Spartan* located at the University of Melbourne. The search required 110GB of RAM.

3.4.1 Base case results

The optimal solution for the instance ISP22_32N_6W results in a total expected cost of $22.94 billons, which corresponds to 20 years of equivalent operation and investment in new transmission lines. The optimal portfolio of lines selected in this case is presented in Table 3.10.

Table 3.10. Optimal investment portfolio for case ISP22_32N_6W

Line	Line ID	Region A	Region B	Rating (MW)		Year asset becomes operational (scenario)
				A to B	B to A	
CNQ-GG Option 1	13	CNQ	GG	550	500	2027 (All)
SQ-CNQ Option 1	14	SQ	CNQ	900	900	2032 (All)
SQ-CNQ Option 2	15	SQ	CNQ	0	300	2027 (All)
CNQ-SQ Option 4	17	SQ	CNQ	1500	1500	2032 (18)
NNSW–SQ Option 1	18	NNSW	SQ	910	1080	2032 (9-18), 2037 (4-8)
NNSW–SQ Option 2	19	NNSW	SQ	550	800	2032 (9-18), 2037 (4-8)
CNSW-NNSW Option 6	27	CNSW	NNSW	2190	1800	2027 (All)
CNSW-NNSW Option 6A	28	CNSW	NNSW	880	1270	2032 (All)
CNSW-SNW Option 1	34	CNSW	SNW	5000	0	2037 (18)
VIC-SNSW Option 1 - VNI West	43	VIC	SNSW	1930	1800	2032 (9-14)
VIC-SNSW Option 6A	45	VIC	SNSW	1930	1800	2032 (1-8,15-17)
TAS-VIC Option 1	48	TAS	VIC	750	750	2032 (All)
TAS-VIC Option 2	49	TAS	VIC	750	750	2032 (1-17), 2037 (18)

The results presented in Table 3.10 are also geographically depicted in Figure 3.11, which, for the sake of illustration, only shows the results for the four original scenarios considered in the ISP 2022 (even if all scenarios were included in the study). In the case of Figure 3.11, 4 out 5 different development paths are presented:

- First row in Figure 3.11 (Slow Scenario ISP 2022): Scenarios 1 to 3
- Second row in Figure 3.11 (Progressive Scenario ISP 2022): Scenarios 9 to 14
- Third row in Figure 3.11 (Step Scenario ISP 2022): Scenarios 15 to 17

- Fourth row in Figure 3.11 (Progressive Scenario ISP 2022): Scenario 18

Scenarios 4 to 8 are represented by a development path similar to the first row in Figure 3.11 except from the active links in year 2037, which also include NNSW–SQ Options 1 and 2 (same as the results in 2037 seen in the third row).

There are a few aspects that must be highlighted from these results. Node 1 (year 2022) does not experience any reinforcements because of the lead time involved in the construction of new transmission lines. However, the decisions to build the relevant transmission lines seen in the pictures for nodes 2, 3, 4 and 5 are made in node 1 (and hence all the investments seen at the "child" nodes 2, 3 , 4 and 5 are the same as the decision was made at the "parent" node 1). This is how the uncertainty is factored in when using a scenario tree: nodes where the tree branches out are influenced by all the future paths that are connected to it. The value seen by the model for the different combinations of investment options in all future paths stemming from a specific node is weighted by the probability of that path and used to determine the optimal decision in the node in question. Then, the decision made in 2022 to build the three lines that become active in 2027 is the one that minimises the expected cost across all the scenarios. Some of these investments anticipate conditions in specific branches of the tree and hedge against negative outcomes in the future.

Table 3.10 highlights a set of transmission investment decisions that are deployed across the horizon that is independent from the specific nodes under analysis, which can be considered the backbone of the reinforcement of the future network. These include CNQ-GG Option 1, SQ-CNQ Option 2 and CNSW-NNSW Option 6 in year 2027 (investment decisions made in 2022), and SQ-CNQ Option 1, CNSW-NNSW Option 6A and TAS-VIC Option 1 in year 2032 (investment decisions made in 2027). Most of the investments look to reinforce QLD and NSW internally, plus the increase in interconnection capacity between VIC and TAS through one corridor of Marinuslink. The regional reinforcements within both QLD and NSW are done progressively, with an increase in intraregional capacity in 2027 and later another in 2032.

From the remaining reinforcements deployed across the scenarios, it can be concluded that the reinforcement of the interconnection capacity between QLD and NSW is driven by the conditions of scenarios Step and Hydrogen Superpower in year 2032. It is also interesting to note that there is an interplay between the options available to interconnect VIC and NSW: in the majority of scenarios VIC-SNSW Option 6A becomes active in 2032, except for those scenarios that contain the transition to the Progressive scenario between 2022 and 2027, in which VIC-SNSW Option 1 - VNI West is chosen in year 2032.

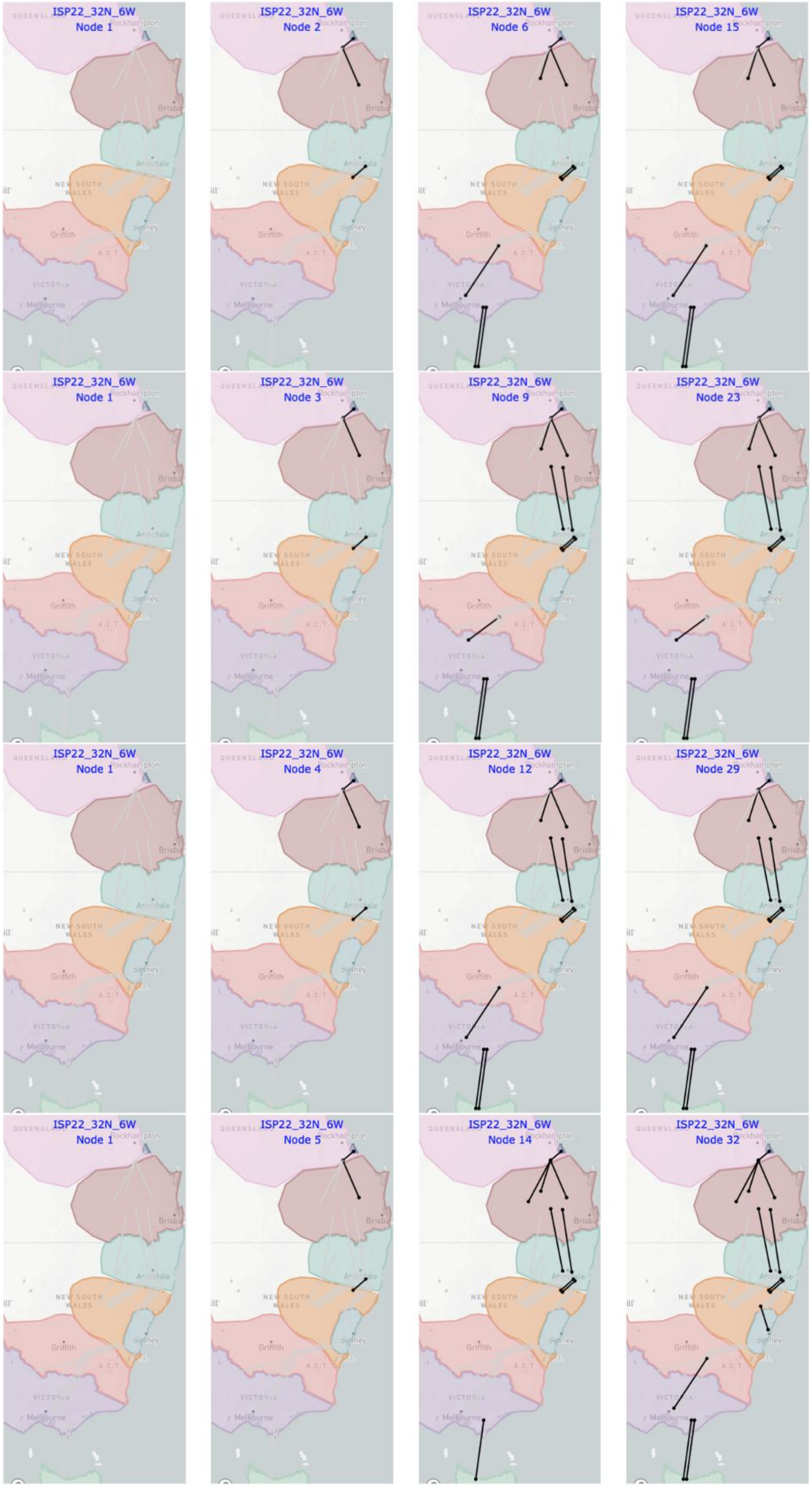


Figure 3.11. Optimal investment options for instance ISP22_32N_6W (node numbers are printed in blue in each map). Each row of the figure displays the results for scenarios 1, 9, 15 and 18, respectively; each column depicts the corresponding year (2022, 2027, 2032 and 2037)

An exhibit that is important in the context of this project is the distribution of costs seen for the scenarios under consideration. This is particularly important in anticipation to the discussion about risk that will be presented in future sections. We use the empirical cumulative distribution function for the cost of all 18 scenarios (paths) as best option for this discussion.

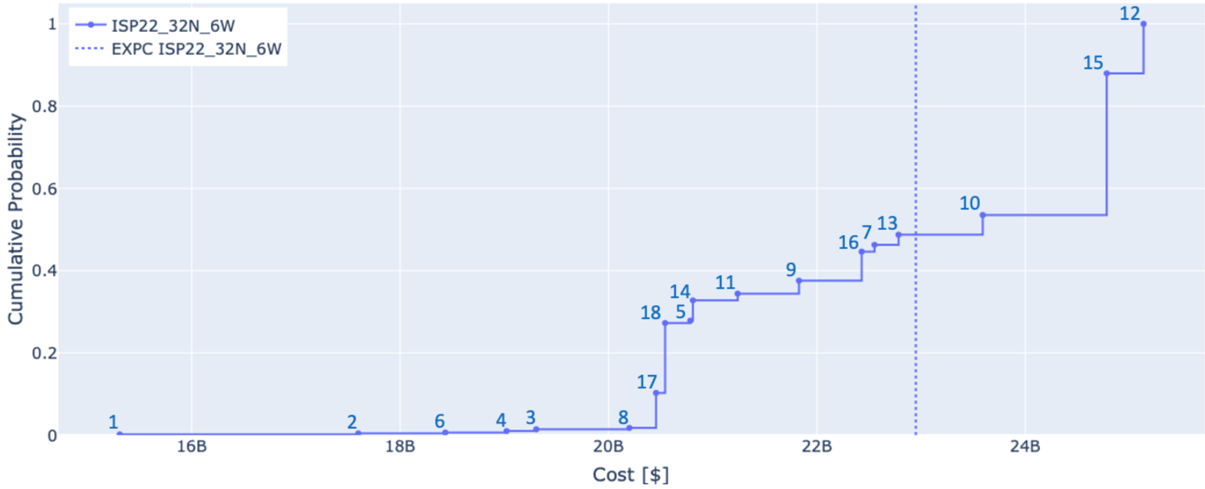


Figure 3.12. Empirical cumulative distribution of scenario cost for the case ISP22_32N_6W

Essentially, when the decisions about new investments are made in each node of the scenario tree, these will result in two components of cost, the annuitised investment needed to deploy the optimal transmission options that year, and the annual costs of operating the system with the new transmission assets. By disaggregating the tree into its scenarios (see Figure 3.10) and taking the cost components for each node, it is possible to calculate the corresponding total costs for each scenario under consideration. The probability of each scenario is known from the definition of the probabilities in the scenario tree (see Table 3.7), so each scenario can be defined by the pair {probability, total cost}. If now the scenarios are organised from cheapest to most costly, and the probabilities are stacked up for successive scenarios, the cumulative distribution of costs is produced.

Figure 3.12 depicts how the costs for each scenario can be organised so as to describe the most costly cases and the total probability associated with those cases (the numbers over the markers correspond to the scenario id). The figure also highlights the expected cost for the portfolio, which shows how it is severely influenced by three most expensive scenarios that concentrate almost 50% of the likelihood of occurrence.

3.4.2 Representation of the operation

A relevant study to conduct starting from the base case presented in the previous section is to analyse the effect of reducing the representation of operation. Here we present the results for the case where the operation is modelled using only *one* representative week (instead of six) per node. This study will be labelled as ISP22_32N_1W. The specific week selected for each node corresponds to the first week for each node as presented in Appendix A.

The cumulative distribution for the 1-week and 6-weeks cases is presented in Figure 3.13. Contrasting both distributions illustrates the effect of the representation of operation on the underlying costs: using one week to model the operation has a tremendous effect on the underlying operation costs, which changes the value certain reinforcements can bring across the scenario tree. A "weaker" representation of operation can make some scenarios cheaper and others more expensive depending on the specific characteristics of the week being utilised in each node. In this case, it results in a substantially smaller expected cost (see red and blue vertical lines in Figure 3.13), as some of the high probability scenarios have a cheaper operational profile than in the case of the 6-weeks case. In the 1-week case the balance between operation and investment costs changes due to the differences in the representation of operation, thus the optimal portfolio of transmission reinforcements for the system is modified.

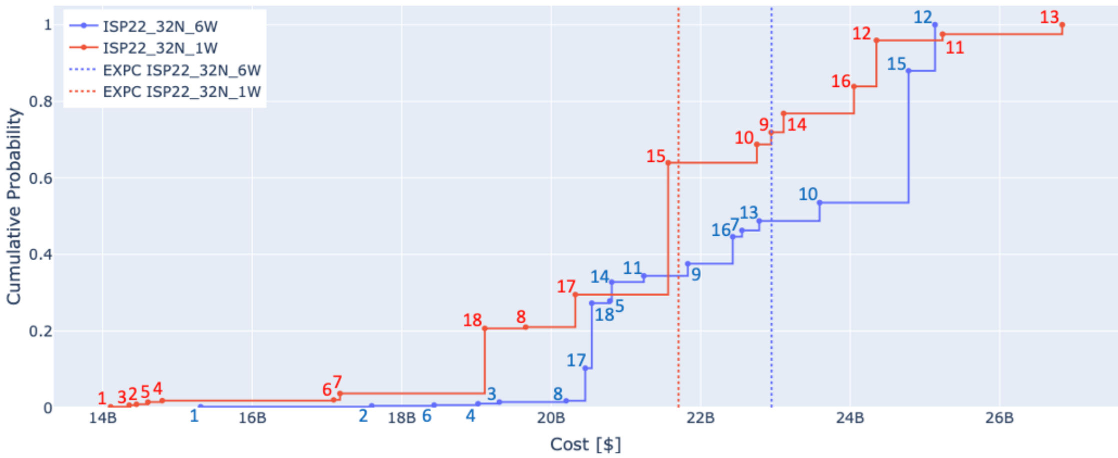


Figure 3.13. Cumulative distribution of scenario cost for the cases ISP22_32_1W and ISP22_32N_6W

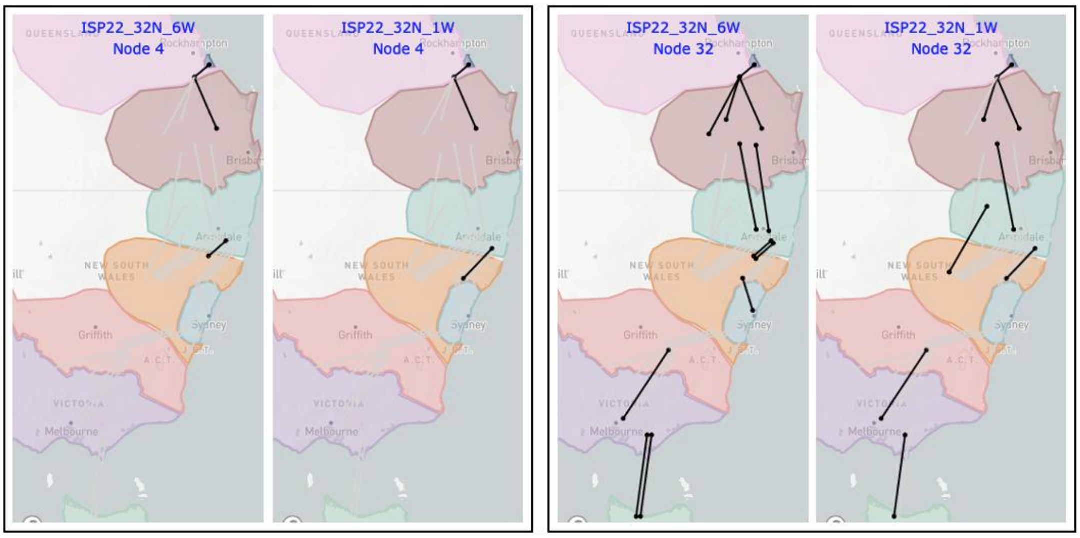


Figure 3.14. Comparison between the active investment for the cases ISP22_32_1W and ISP22_32N_6W in nodes 4 (left) and 32 (right)

Figure 3.14 contrasts the investments active in node 4 and node 32 for the cases under analysis. In this case, both approaches to represent of operation effectively push forward similar investment options in 2027, with only one reinforcement differing between the two cases: the transmission line connecting NNSW and CNSW. The 1-week representation proceeds CNSW-NNSW Option 7 which is cheaper and has a lower rating than the reinforcement installed in the 6-week representation, CNSW-NNSW Option 6. Also, it is worth mentioning that in both cases 5 different development paths are observed between 2022 and 2037[8]. It can be stated that the 6-week case results are more accurate than those seen for the 1-week case, as they better represent the underlying operation of the system. This is easy to prove, since it is possible to obtain the optimal investment portfolio for the 1-week case and use it to simulate the operation of the 6-week case. With the results of the operation, it is possible to calculate the distribution of total costs of investment and operation for the 6-weeks case using the 1-week investment portfolio. This case study will be labelled "6W_1WINV". Figure 3.15 clearly shows how the optimal investment decisions of the 1-week case, although cheaper, yield extremely bad results when used to operate the system under the conditions determined by the 6-week case. These results stem from the high amounts of unserved energy observed in some nodes of the scenario tree (e.g., scenario 8 experiences around 3.2 TWh of unserved energy) due to the inadequate network development to cope with the operational conditions described in the 6-week case. Since the market price cap is used to penalise unserved energy in the objective function, the total costs of operation see a very substantial increase due to the unserved energy.

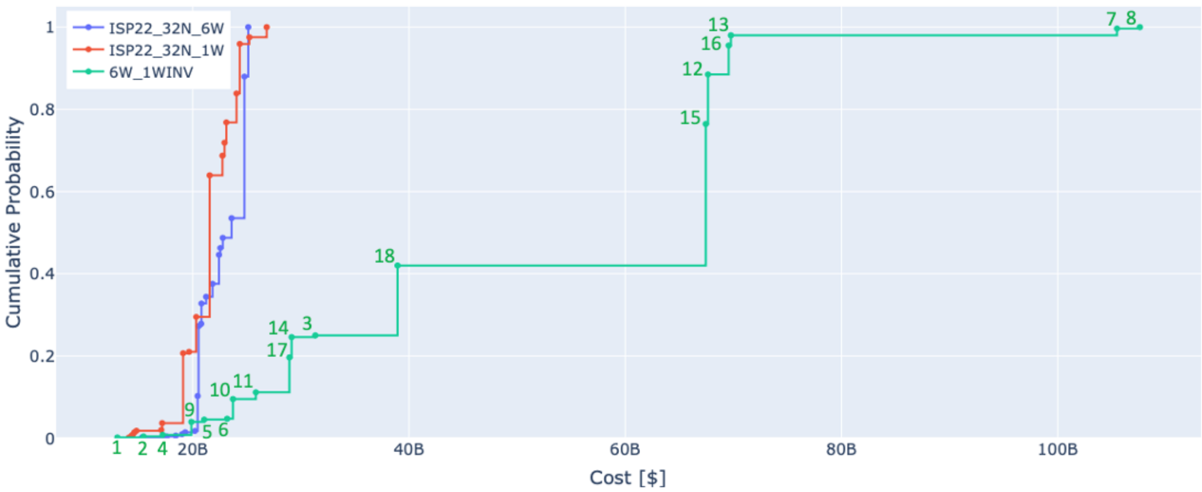


Figure 3.15. Cumulative distribution of scenario total costs for case 6W_1WINV (green) which corresponds to applying the optimal investment decisions of the 1-week case to the 6-week case

[8] Identifying a suitable operational representation of the problem in order to strike the best possible outcomes between accuracy of the results and computational cost is something that could be considered further in follow-up projects.

3.4.3 Role of additional storage

As described in section 3.3.1, storage is already present in the optimal development path of the ISP 2022. Thus, there already is a very substantial amount of storage deployed across the nodes in the scenario tree. However, in this specific case study we let the model decide if additional storage (with 4 hours storage capacity) could help finding a lower expected investment and operation cost for the system. This specific case, which considers batteries as an investment option, is labelled ISP22_32N_1W_BAT. As a side note, the problem that considers batteries as an investment option took more than three times longer than the original case without battery investment.

Before digging into the results of the investment selection, let us observe first how this option to invest in batteries modifies the distribution of costs for the different scenarios. By inspecting Figure 3.16, it can be seen that there are only little changes compared to the case without BESS investment options. The changes in the expected cost does favour ISP22_32N_1W_BAT, which displays expected costs that are $72 million (so some 0.3%) cheaper than case ISP22_32N_1W.

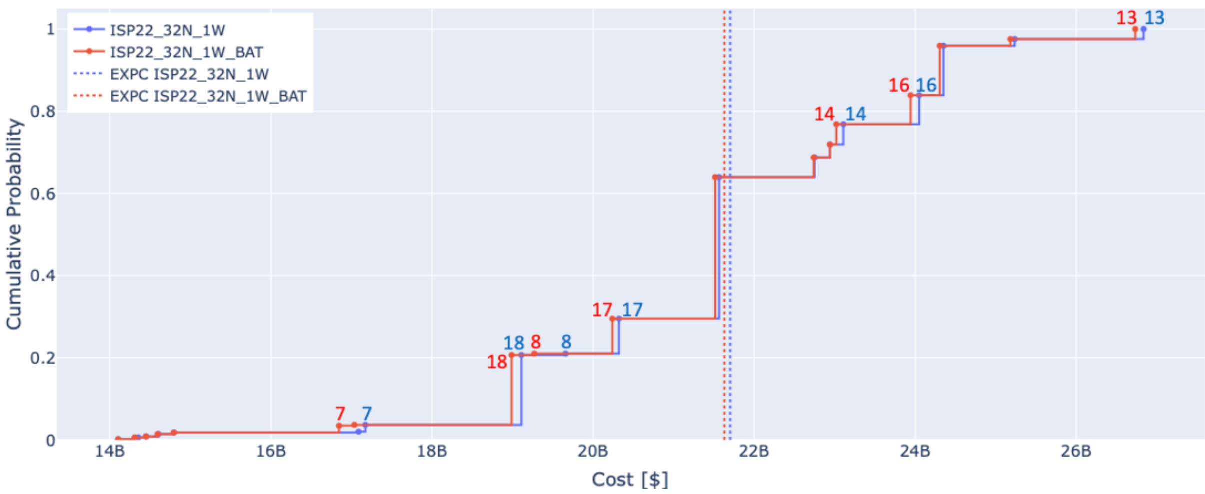


Figure 3.16. Cumulative distribution of scenario costs for cases ISP22_32N_1W and ISP22_32N_1W_BAT

By inspecting the results for case ISP22_32N_1W_BAT it appears that the future storage capacities obtained from the ISP 2022 and used as input data suit the system requirements under a stochastic framework. There are instances where additional storage is installed before 2037, and even then, the storage capacity that is added to the system is relatively low. There are no scenarios displaying the deployment of storage capable to defer investment in transmission. However, the capacity to co-optimise both technologies does provide some flexibility to achieve a better techno-economic performance in many scenarios, in general associated with scenarios where some of the nodes belong to the step or hydrogen superpower scenario. The total cost of investing and operating scenario 7 reduces around 1.9%, or in case of scenario 17 a reduction of 0.4%. Figure 3.17 presents the evolution of the investment in transmission and storage for scenario 17, where one can appreciate how the new lines do not change and the new storage assets are located in places that enable the system to reduce costs by arbitraging energy.

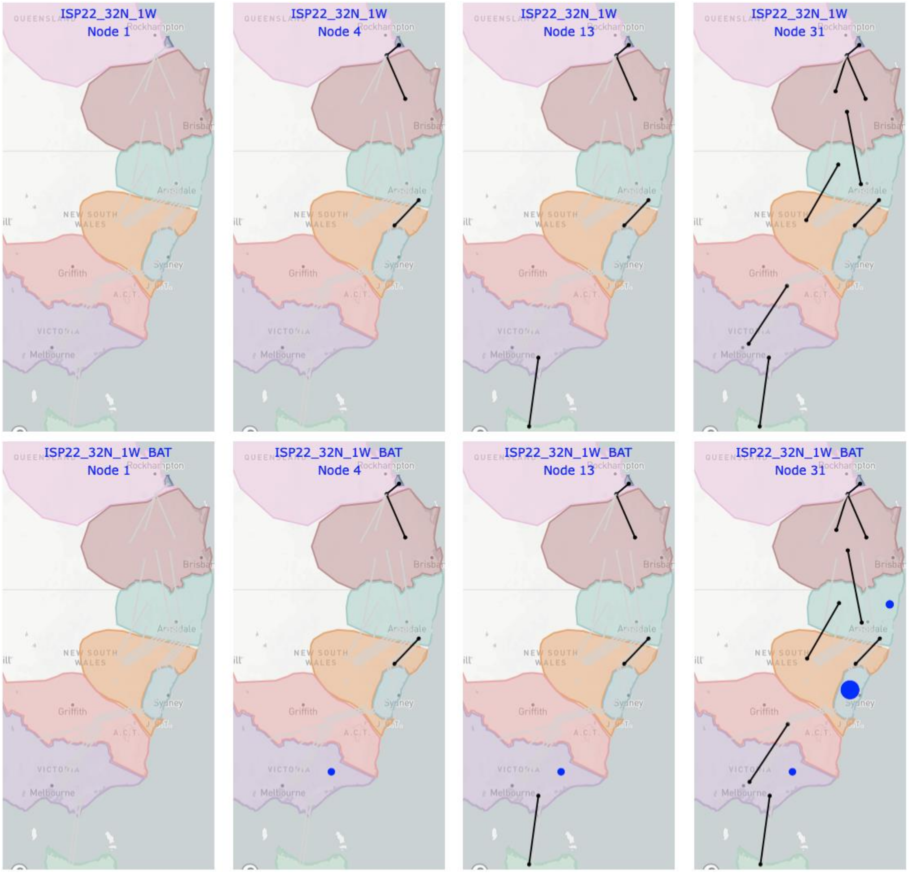


Figure 3.17. Effect of co-optimising storage and transmission on the results for scenario 17. The upper row of results corresponds to the case considering only transmission options and lower row the case considering both BESS and transmission investment options. Columns from left to right correspond to years 2022, 2027, 2032 and 2037, respectively.

4 Deterministic planning

Most if not all transmission expansion methodologies used around the world by system planners are based on deterministic planning models (see Section 2.1.3), where many scenarios are analysed from a deterministic perspective. In some cases, the most advanced methodologies then use an additional metric to select the optimal plan for the system based on the results for the deterministic studies. Decisions made using the information obtained across multiple deterministic scenarios are being used in the UK, Australia and at least one jurisdiction in the US, through the so-called least-worst regret (LWR) and, more recently, least-worst weighted regret (LWWR). An in-depth analysis of these two approaches was conducted in [3], [4] for NGESO in the UK.

This section presents a quantitative comparison between deterministic-based LWR and LWWR metrics and our stochastic planning approach, aiming to understand the advantages and disadvantages of each approach.

4.1 Deterministic based metrics: LWR & LWWR

LWR decisions operate based on the use of regrets as the indicator to the proximity to the optimal solution. The mechanics of such approach are exemplified in the following steps:

i. Select several scenarios to analyse and investment options to study.
ii. For each scenario determine the optimal portfolio of investment options that minimises the cost of that scenario.
iii. Using all the optimal portfolios (which, as it is a multistage plan, we will call *development paths*) found in the previous set, determine the investment and operational cost resulting from applying each of those development paths to each of the scenarios under consideration. These costs can be organised in the form of a matrix (Figure 4.1a, numbers in the figure are purely illustrative).
iv. Using the matrix of costs, determine the specific development path from the set of development paths found before that produces the lowest cost for each scenario (Figure 4.1b-c).
v. Using such cost as reference, calculate the regret of applying each development path for that scenario by calculating the difference between the cost of applying that development path and the reference cost (Figure 4.1b-c).
vi. Now, looking at each development path, determine the worst (maximum) regret (that is, the maximum possible value in each regret column) that such development path can produce across all scenarios (Figure 4.1d).
vii. The vector of worst regrets associated to each development path can then be minimised to determine what development path produces the “least-worst” regret in the set of paths under consideration (Figure 4.1e).

	COST [$]			REGRET [$]		
	Dev. Path 1	Dev. Path 2	Dev. Path 3	Dev. Path 1	Dev. Path 2	Dev. Path 3
Sce 1	150	200	279			
Sce 2	357	260	394			
Sce 3	280	180	146			

a) Original cost matrix

	COST [$]			REGRET [$]		
	Dev. Path 1	Dev. Path 2	Dev. Path 3	Dev. Path 1	Dev. Path 2	Dev. Path 3
Sce 1	**150**	200	279	0	50	129
Sce 2	357	260	394			
Sce 3	280	180	146			

b) Determination of reference cost for scenario 1 and the regrets across paths

	COST [$]			REGRET [$]		
	Dev. Path 1	Dev. Path 2	Dev. Path 3	Dev. Path 1	Dev. Path 2	Dev. Path 3
Sce 1	**150**	200	279	0	50	129
Sce 2	357	**260**	394	97	0	134
Sce 3	280	180	**146**	134	34	0

c) Reference cost for all scenarios and corresponding regrets across paths

	COST [$]			REGRET [$]		
	Dev. Path 1	Dev. Path 2	Dev. Path 3	Dev. Path 1	Dev. Path 2	Dev. Path 3
Sce 1	**150**	200	279	0	50	129
Sce 2	357	**260**	394	97	0	134
Sce 3	280	180	**146**	134	34	0
				134	**50**	**134**

d) Worst regret determination for each development path

	COST [$]			REGRET [$]		
	Dev. Path 1	Dev. Path 2	Dev. Path 3	Dev. Path 1	Dev. Path 2	Dev. Path 3
Sce. 1	**150**	200	279	0	50	129
Sce. 2	357	**260**	394	97	0	134
Sce. 3	280	180	**146**	134	34	0
				134	**50**	**134**

e) Path selection based on the minimum worst regret across development paths

Figure 4.1. Calculation steps for an approach that utilises LWR based on illustrative numbers.

A variant to the methodology presented before corresponds to multiplying the costs and regrets presented in Figure 4.1c by the probability of each scenario before doing the calculations associated to Figure 4.1d-e. This approach yields the least-worst weighted regret (LWWR) solution and aims to incorporate scenario probabilities in the LWR approach that otherwise manipulates results across scenarios assuming to be probability-agnostic (which is equivalent to assuming the same probability of occurrence in all scenarios).

		Weighted COST [$]			Weighted REGRET [$]		
Prob.		**Dev. Path 1**	**Dev. Path 2**	**Dev. Path 3**	**Dev. Path 1**	**Dev. Path 2**	**Dev. Path 3**
0.8	**Sce. 1**	120	160	223.2	0	40	103.2
0.1	**Sce. 2**	35.7	26	39.4	9.7	0	13.4
0.1	**Sce. 3**	28	18	14.6	13.4	3.4	0
					13.4	**40**	**103.2**

Figure 4.2. Example for the calculation of LWWR

Figure 4.2 shows how the scenario probabilities are applied to the same case presented in Figure 4.1 to calculate the optimal development path according to LWWR. It is straightforward to see that the decision made through the use of LWR is to select development path 2 while LWWR selects development path 1.

The approach to calculate LWR/LWWR presented in (i)-(vii) describes the general mechanisms of the procedure. However, there are various ways to define the candidate development paths. In (i)-(vii), the matrix of costs is built by determining the cost of applying the full development path found by optimising each scenario in a deterministic manner. This is something that system operators that use LWR/LWWR, like NGESO or AEMO, do differently.

For instance, after NGESO [39] determines a development path for each scenario through deterministic optimisation (or an equivalent procedure/heuristic), it focuses on the transmission options that are selected to be deployed at their 'earliest-in-service date' in the different scenarios. These investments are critical as if they are not proceeded immediately, they will not become available at the time they are supposed to be active to achieve the optimality in each deterministic scenario.

All critical investment options are gathered, and each scenario is run again fixing the non-critical options. The new set of deterministic runs considers all the combinations of delaying 1 year or not delaying each critical investment option (basically, if there are two critical investment options, there would be four runs per scenario under consideration: delaying both, not delaying any, delaying one and not delaying the other, and vice versa).

The new set of deterministic runs would produce several development paths (as a matter of fact it would be 2^n development paths, where n is the number of critical investment options). A case with four scenarios and n critical development path would result in a cost matrix (see

Figure 4.1a) of dimensions 4x2^n. Then the LWR/LWWR procedure can be applied in the same way as specified in (iv)-(vii).

This shows that the LWR/LWWR methodology can be applied in different ways depending on the type of decision that the planner wants to make.

The idea now is to understand how the stochastic results found for case ISP22_32_6W are compared to a deterministic based approach like LWR/LWWR in which we follow, in terms of specific implementation, the generic mechanism presented in the steps (i)-(vii) above.

4.2 Deterministic study

In the results presented in this section we use the generic approach described in steps (i)-(iii) to calculate the deterministic development paths, as opposed to the more specific methodologies used by the NGESO described before. The deterministic scenarios that are considered come from the disaggregation of the 18 scenarios that give form to the 32-node scenario tree presented in Figure 3.10, which was used to run the study ISP22_32N_6W. The disaggregation is depicted in Figure 4.3, and shows how each of the deterministic scenarios is formed and what the probability of that scenario is (as presented in Figure 3.10 and Table 3.7).

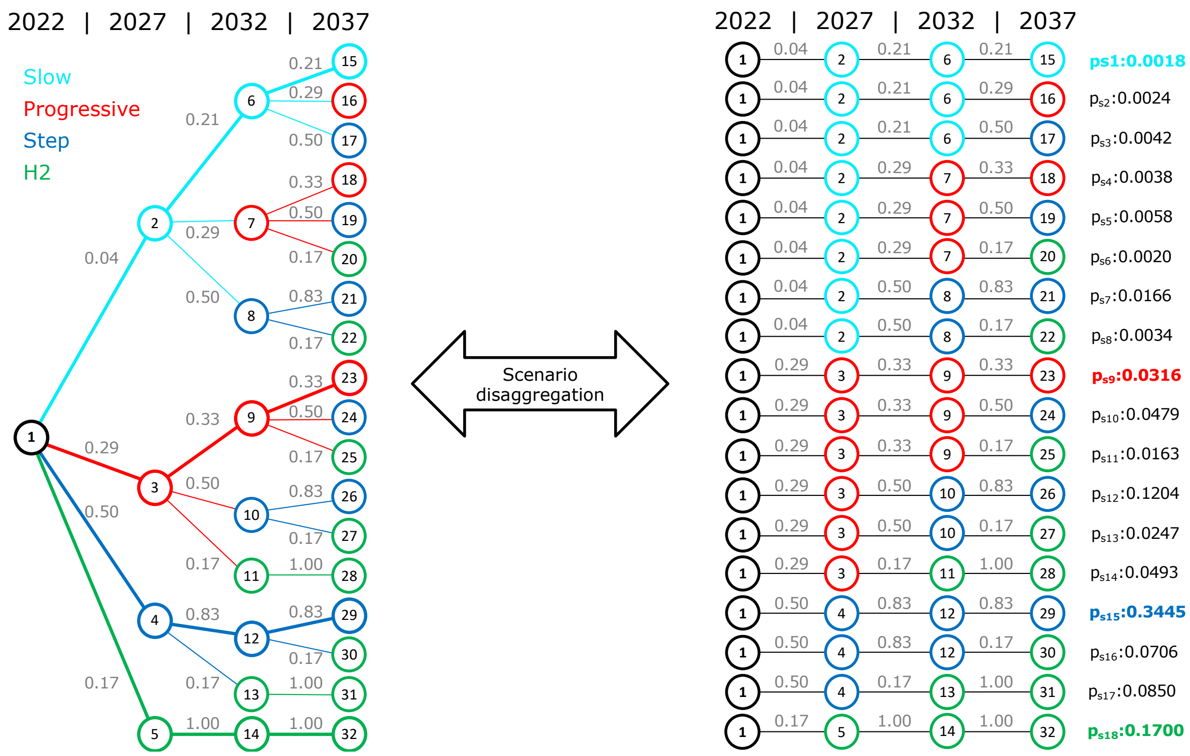


Figure 4.3. Scenario disaggregation

Each of the 18 scenarios on the right of Figure 4.3 are solved as deterministic optimisation problems (the probability of transition from one node to the next are set to 1 to solve the deterministic problem) using the same set of transmission investment options that have been used so far for the stochastic problems ISP22_32N_6W and ISP22_32N_1W. This will yield a development path for each scenario, which are numbered following the order of the scenarios. Then the optimisation of each scenario is run again, but now imposing the development paths found for each deterministic scenario (essentially, the optimisation at this point only considers operation variables, as all the investment options are fixed). This yields the cost matrix needed to determine the regrets. This procedure is depicted in Figure 4.4.

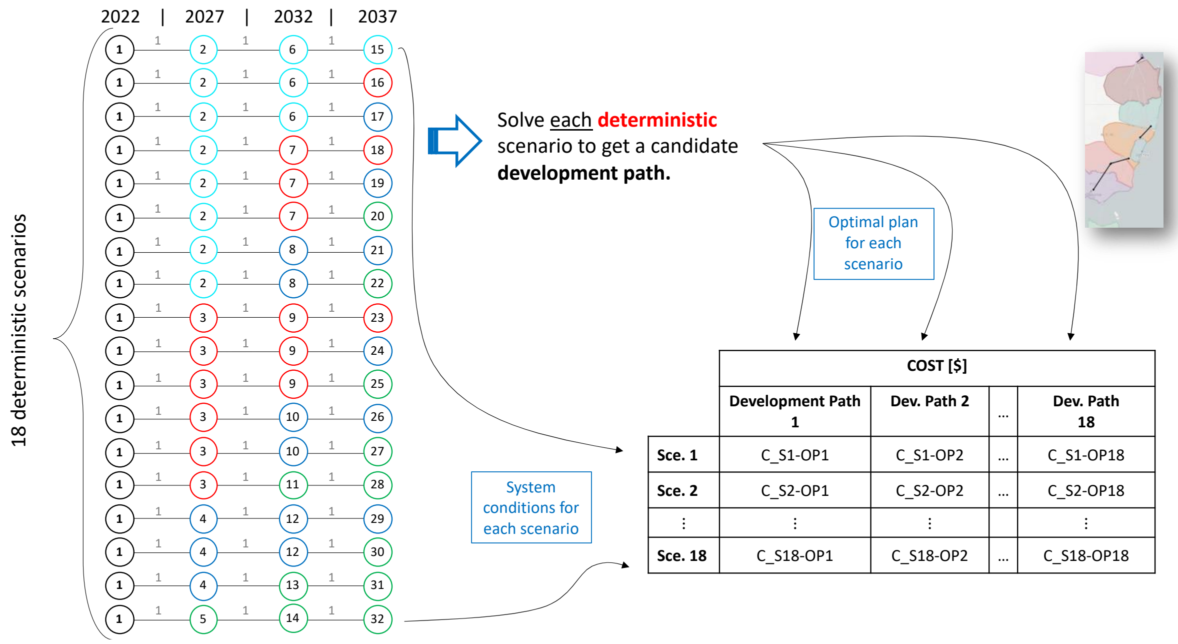


Figure 4.4. Procedure to calculate the 18 deterministic development paths based on the disaggregated 32-node scenario tree

The process of determining the development paths for each scenario is relatively quick, as the resulting optimisation problem is much smaller than a stochastic problem. When it comes to determining the costs of operation and investment by imposing a certain development path (fixing the investment variables), the solutions of the resulting optimisation problems are found even faster. The largest bottleneck actually becomes the reading of input databases. As a reference, a standard 16Gb laptop computer can calculate the development paths and find the cost matrix within 24 hours (for the conditions of the problems under consideration), where the process of reading the databases and creating each deterministic optimisation problem takes up to 15 times longer than the time needed to solve it.

The cost matrix is presented in Figure 4.5. The numbers have been rounded to the closest integer value for an easier interpretation of results. The diagonal represents the total cost found in the process of determining the development paths for each scenario. For that reason, for any given scenario, the value in the diagonal of the matrix is the smallest possible. It is worth checking that this value is also smaller than the result found for each scenario for the stochastic approach (case ISP22_32N_6W), as seen in Figure 3.12. For instance, the value in the diagonal for scenario 10 is $21.3 billion, which results from finding the best investment options for the conditions in that scenario. On the other hand, the stochastic result for scenario 10 was very close to $24 billion. This is because the stochastic solution factors in what is convenient for *all* the scenarios potentially unfolding in the form of the 32N scenario tree, which leads to a *compromise* solution for all scenarios (thus possibly more costly than each specific corresponding deterministic counterpart).

	SCENARIO	COSTS (B$)																	
		DP1	DP2	DP3	DP4	DP5	DP6	DP7	DP8	DP9	DP10	DP11	DP12	DP13	DP14	DP15	DP16	DP17	DP18
SLOW	S1	12	13	13	13	13	14	15	16	13	13	14	15	16	16	15	16	16	16
	S2	29	15	16	15	16	17	17	18	15	16	17	17	18	18	17	18	18	19
	S3	69	31	18	31	18	18	19	20	31	18	18	19	20	20	19	19	20	20
	S4	31	17	17	17	17	18	18	19	17	17	18	18	19	20	18	19	19	20
	S5	71	32	19	32	19	20	20	21	32	19	20	20	21	22	20	21	21	22
	S6	79	36	20	36	20	17	21	18	36	20	17	21	18	18	21	18	18	18
	S7	180	142	129	142	129	129	22	23	142	129	129	22	23	64	22	23	64	64
	S8	189	146	130	146	130	126	23	20	146	130	126	23	20	61	23	20	60	61
PROGRESSIVE	S9	33	19	20	19	20	20	21	21	19	20	20	21	21	22	21	22	22	22
	S10	73	35	21	35	21	22	22	23	35	21	22	22	23	23	22	23	24	24
	S11	82	39	23	39	23	19	24	20	39	23	19	24	20	20	24	20	20	21
	S12	183	145	131	145	131	132	24	25	145	131	132	24	25	66	24	25	66	67
	S13	192	148	133	148	133	129	26	22	148	133	129	26	22	63	26	22	63	63
	S14	172	129	113	129	113	106	26	22	129	113	106	26	22	19	26	22	19	20
STEP	S15	183	144	131	144	131	131	24	25	144	131	132	24	25	66	24	25	66	66
	S16	191	148	132	148	132	128	25	22	148	132	129	25	22	63	25	21	62	63
	S17	172	129	113	129	113	105	26	22	129	113	106	26	22	20	26	22	19	20
H2	S18	179	136	120	136	120	116	33	29	136	120	112	33	29	26	32	32	29	20

Figure 4.5. Cost matrix

Following the steps (iv)-(vii) it is then straightforward to identify the LWR solution for this study. Figure 4.6 presents the full calculations using the LWR metric (similar to Figure 4.1e). The regrets have been rounded including 1 decimal to provide more details about the worst regret minimisation process. In this particular case, the development path found for scenario 8 and scenario 13 are chosen by means of the LWR metric. Both scenarios have the same deterministic development path (both scenarios are equal in all years except for year 2027 where scenario 8 is slow and scenario 13 is progressive), thus the worst regrets are the same, and occur in the case where the development path is deployed in the system, but scenario 18 (H_2 superpower) unfolds.

As it was described before, applying LWWR instead of LWR is straightforward. Using the probabilities for each scenario, the cost matrix is weighted and then steps (iv)-(vii) are applied. The results are shown in Figure 4.7, which shows that, in this particular case, applying scenario probabilities does not change the decision in favour of the development path found by LWR. The optimal development path according to LWR/LWWR is presented in Figure 4.8.

COSTS (B$)

SCENARIO	DP1	DP2	DP3	DP4	DP5	DP6	DP7	DP8	DP9	DP10	DP11	DP12	DP13	DP14	DP15	DP16	DP17	DP18
S1	**12**	13	13	13	13	14	15	16	13	13	14	15	16	16	15	16	16	16
S2	29	**15**	16	15	16	17	17	18	15	16	17	17	18	18	17	18	18	19
S3	69	31	**18**	31	18	18	19	20	31	18	18	19	20	20	19	19	20	20
S4	31	17	17	**17**	17	18	18	19	17	17	18	18	19	20	18	19	19	20
S5	71	32	19	32	**19**	20	20	21	32	19	20	20	21	22	20	21	21	22
S6	79	36	20	36	20	**17**	21	18	36	20	17	21	18	18	21	18	18	18
S7	180	142	129	142	129	129	**22**	23	142	129	129	22	23	64	22	23	64	64
S8	189	146	130	146	130	126	23	**20**	146	130	126	23	20	61	23	20	60	61
S9	33	19	20	19	20	20	21	21	**19**	20	20	21	21	22	21	22	22	22
S10	73	35	21	35	21	22	22	23	35	**21**	22	22	23	23	22	23	24	24
S11	82	39	23	39	23	19	24	20	39	23	**19**	24	20	20	24	20	20	21
S12	183	145	131	145	131	132	24	25	145	131	132	**24**	25	66	24	25	66	67
S13	192	148	133	148	133	129	26	22	148	133	129	26	**22**	63	26	22	63	63
S14	172	129	113	129	113	106	26	22	129	113	106	26	22	**19**	26	22	19	20
S15	183	144	131	144	131	131	24	25	144	131	132	24	25	66	**24**	25	66	66
S16	191	148	132	148	132	128	25	22	148	132	129	25	22	63	25	**21**	62	63
S17	172	129	113	129	113	105	26	22	129	113	106	26	22	20	26	22	**19**	20
S18	179	136	120	136	120	116	33	29	136	120	112	33	29	26	32	32	29	**20**

REGRETS (B$)

SCENARIO	DP1	DP2	DP3	DP4	DP5	DP6	DP7	DP8	DP9	DP10	DP11	DP12	DP13	DP14	DP15	DP16	DP17	DP18
S1	0.0	0.4	1.1	0.4	1.1	2.0	2.3	**3.2**	0.4	1.1	2.1	2.3	**3.2**	3.9	2.3	3.2	3.5	4.1
S2	14.0	0.0	0.7	0.0	0.7	1.4	1.8	**2.5**	0.0	0.7	1.4	1.8	**2.5**	3.2	1.8	2.5	2.8	3.4
S3	51.7	13.6	0.0	13.6	0.0	0.8	1.2	**2.0**	13.6	0.0	0.9	1.2	**2.0**	2.7	1.2	1.9	2.2	2.8
S4	14.0	0.0	0.7	0.0	0.7	1.3	1.8	**2.4**	0.0	0.7	1.4	1.8	**2.4**	3.1	1.8	2.4	2.7	3.3
S5	51.7	13.6	0.0	13.6	0.0	0.7	1.1	**1.9**	13.6	0.0	0.8	1.1	**1.9**	2.6	1.2	1.8	2.1	2.7
S6	62.8	19.7	3.8	19.7	3.8	0.0	4.7	**1.2**	19.7	3.8	0.1	4.7	**1.2**	1.6	4.7	1.1	1.1	1.7
S7	158.4	120.3	106.7	120.3	106.7	107.4	0.0	**0.7**	120.3	106.7	107.4	0.0	**0.7**	42.1	0.0	0.6	41.7	42.3
S8	169.7	126.5	110.7	126.5	110.7	106.8	3.6	**0.0**	126.5	110.7	106.8	3.6	**0.0**	41.3	3.6	0.0	40.8	41.4
S9	14.0	0.0	0.7	0.0	0.7	1.4	1.8	**2.4**	0.0	0.7	1.4	1.8	**2.4**	2.7	1.8	2.5	2.9	3.2
S10	51.7	13.6	0.0	13.6	0.0	0.9	1.1	**1.9**	13.6	0.0	0.8	1.1	**1.9**	2.1	1.2	2.0	2.3	2.7
S11	62.8	19.6	3.7	19.6	3.7	0.1	4.6	**1.1**	19.6	3.7	0.0	4.6	**1.1**	1.1	4.6	1.2	1.2	1.6
S12	158.4	120.3	106.7	120.3	106.7	107.5	0.0	**0.7**	120.3	106.7	107.5	0.0	**0.7**	41.7	0.0	0.8	41.9	42.2
S13	169.6	126.5	110.6	126.5	110.6	106.9	3.6	**0.0**	126.5	110.6	106.8	3.6	**0.0**	40.8	3.6	0.1	40.9	41.3
S14	153.0	109.9	94.0	109.9	94.0	86.5	6.7	**3.2**	109.9	94.0	86.5	6.7	**3.2**	0.0	6.5	3.1	0.2	0.5
S15	158.4	120.3	106.7	120.3	106.7	107.2	0.0	**0.7**	120.3	106.7	107.5	0.0	**0.7**	42.2	0.0	0.4	41.5	42.3
S16	169.9	126.8	110.9	126.8	110.9	106.8	3.9	**0.3**	126.8	110.9	107.1	3.9	**0.3**	41.5	3.8	0.0	40.8	41.7
S17	153.3	110.1	94.2	110.1	94.2	86.4	7.0	**3.4**	110.1	94.2	86.7	7.0	**3.4**	0.7	6.7	2.9	0.0	0.8
S18	158.7	115.5	99.7	115.5	99.7	95.4	12.4	**8.8**	115.5	99.7	92.1	12.4	**8.8**	5.7	12.1	11.8	8.9	0.0
	169.9	126.8	110.9	126.8	110.9	107.5	12.4	**8.8**	126.8	110.9	107.5	12.4	**8.8**	42.2	12.1	11.8	41.9	42.3

Figure 4.6. Full LWR calculations

WEIGHTED COSTS (B$)

PROB.		DP1	DP2	DP3	DP4	DP5	DP6	DP7	DP8	DP9	DP10	DP11	DP12	DP13	DP14	DP15	DP16	DP17	DP18
0.0018	S1	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.02	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
0.0024	S2	0.07	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05
0.0042	S3	0.29	0.13	0.07	0.13	0.07	0.08	0.08	0.08	0.13	0.07	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.09
0.0038	S4	0.12	0.06	0.07	0.06	0.07	0.07	0.07	0.07	0.06	0.07	0.07	0.07	0.07	0.08	0.07	0.07	0.07	0.08
0.0058	S5	0.41	0.19	0.11	0.19	0.11	0.11	0.12	0.12	0.19	0.11	0.11	0.12	0.12	0.12	0.12	0.12	0.12	0.13
0.0020	S6	0.16	0.07	0.04	0.07	0.04	0.03	0.04	0.04	0.07	0.04	0.03	0.04	0.04	0.04	0.04	0.03	0.04	0.04
0.0166	S7	2.99	2.36	2.14	2.36	2.14	2.15	0.36	0.37	2.36	2.14	2.15	0.36	0.37	1.06	0.36	0.37	1.06	1.07
0.0034	S8	0.64	0.50	0.44	0.50	0.44	0.43	0.08	0.07	0.50	0.44	0.43	0.08	0.07	0.21	0.08	0.07	0.21	0.21
0.0316	S9	1.04	0.60	0.62	0.60	0.62	0.64	0.66	0.68	0.60	0.62	0.64	0.66	0.68	0.68	0.66	0.68	0.69	0.70
0.0479	S10	3.49	1.67	1.02	1.67	1.02	1.06	1.07	1.11	1.67	1.02	1.06	1.07	1.11	1.12	1.08	1.11	1.13	1.15
0.0163	S11	1.33	0.63	0.37	0.63	0.37	0.31	0.39	0.33	0.63	0.37	0.31	0.39	0.33	0.33	0.39	0.33	0.33	0.34
0.1204	S12	21.99	17.40	15.77	17.40	15.77	15.86	2.92	3.00	17.40	15.77	15.85	2.92	3.00	7.94	2.93	3.01	7.96	8.01
0.0247	S13	4.72	3.66	3.27	3.66	3.27	3.18	0.63	0.54	3.66	3.27	3.17	0.63	0.54	1.55	0.63	0.54	1.55	1.56
0.0493	S14	8.50	6.37	5.59	6.37	5.59	5.22	1.28	1.11	6.37	5.59	5.21	1.28	1.11	0.95	1.27	1.10	0.96	0.98
0.3445	S15	62.88	49.74	45.07	49.74	45.07	45.23	8.31	8.54	49.74	45.07	45.32	8.31	8.54	22.83	8.31	8.44	22.60	22.89
0.0706	S16	13.50	10.46	9.34	10.46	9.34	9.05	1.79	1.54	10.46	9.34	9.07	1.79	1.54	4.44	1.78	1.52	4.40	4.46
0.0850	S17	14.64	10.97	9.62	10.97	9.62	8.95	2.20	1.90	10.97	9.62	8.98	2.20	1.90	1.66	2.18	1.86	1.61	1.68
0.1700	S18	30.44	23.10	20.40	23.10	20.40	19.68	5.56	4.96	23.10	20.40	19.11	5.56	4.96	4.43	5.52	5.47	4.97	3.46

WEIGTHED REGRETS (B$)

PROB.		DP1	DP2	DP3	DP4	DP5	DP6	DP7	**DP8**	DP9	DP10	DP11	DP12	**DP13**	DP14	DP15	DP16	DP17	DP18
0.0018	S1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.01**	0.00	0.00	0.00	0.00	**0.01**	0.01	0.00	0.01	0.01	0.01
0.0024	S2	0.03	0.00	0.00	0.00	0.00	0.00	0.00	**0.01**	0.00	0.00	0.00	0.00	**0.01**	0.01	0.00	0.01	0.01	0.01
0.0042	S3	0.22	0.06	0.00	0.06	0.00	0.00	0.00	**0.01**	0.06	0.00	0.00	0.00	**0.01**	0.01	0.00	0.01	0.01	0.01
0.0038	S4	0.05	0.00	0.00	0.00	0.00	0.00	0.01	**0.01**	0.00	0.00	0.01	0.01	**0.01**	0.01	0.01	0.01	0.01	0.01
0.0058	S5	0.30	0.08	0.00	0.08	0.00	0.00	0.01	**0.01**	0.08	0.00	0.00	0.01	**0.01**	0.01	0.01	0.01	0.01	0.02
0.0020	S6	0.12	0.04	0.01	0.04	0.01	0.00	0.01	**0.00**	0.04	0.01	0.00	0.01	**0.00**	0.00	0.01	0.00	0.00	0.00
0.0166	S7	2.63	2.00	1.77	2.00	1.77	1.78	0.00	**0.01**	2.00	1.77	1.78	0.00	**0.01**	0.70	0.00	0.01	0.69	0.70
0.0034	S8	0.58	0.43	0.38	0.43	0.38	0.36	0.01	**0.00**	0.43	0.38	0.36	0.01	**0.00**	0.14	0.01	0.00	0.14	0.14
0.0316	S9	0.44	0.00	0.02	0.00	0.02	0.05	0.06	**0.08**	0.00	0.02	0.04	0.06	**0.08**	0.09	0.06	0.08	0.09	0.10
0.0479	S10	2.47	0.65	0.00	0.65	0.00	0.04	0.05	**0.09**	0.65	0.00	0.04	0.05	**0.09**	0.10	0.06	0.09	0.11	0.13
0.0163	S11	1.02	0.32	0.06	0.32	0.06	0.00	0.07	**0.02**	0.32	0.06	0.00	0.07	**0.02**	0.02	0.07	0.02	0.02	0.03
0.1204	S12	19.07	14.48	12.85	14.48	12.85	12.94	0.00	**0.08**	14.48	12.85	12.93	0.00	**0.08**	5.02	0.00	0.09	5.04	5.08
0.0247	S13	4.18	3.12	2.73	3.12	2.73	2.63	0.09	**0.00**	3.12	2.73	2.63	0.09	**0.00**	1.00	0.09	0.00	1.01	1.02
0.0493	S14	7.55	5.42	4.64	5.42	4.64	4.27	0.33	**0.16**	5.42	4.64	4.26	0.33	**0.16**	0.00	0.32	0.15	0.01	0.03
0.3445	S15	54.58	41.44	36.77	41.44	36.77	36.92	0.00	**0.23**	41.44	36.77	37.02	0.00	**0.23**	14.52	0.00	0.13	14.30	14.58
0.0706	S16	11.99	8.94	7.82	8.94	7.82	7.54	0.27	**0.02**	8.94	7.82	7.55	0.27	**0.02**	2.93	0.27	0.00	2.88	2.94
0.0850	S17	13.03	9.36	8.01	9.36	8.01	7.35	0.59	**0.29**	9.36	8.01	7.37	0.59	**0.29**	0.06	0.57	0.25	0.00	0.07
0.1700	S18	26.98	19.64	16.94	19.64	16.94	16.22	2.10	**1.50**	19.64	16.94	15.65	2.10	**1.50**	0.98	2.06	2.01	1.51	0.00
		54.58	41.44	36.77	41.44	36.77	36.92	2.10	**1.50**	41.44	36.77	37.02	2.10	**1.50**	14.52	2.06	2.01	14.30	14.58

Figure 4.7. Full LWWR calculations

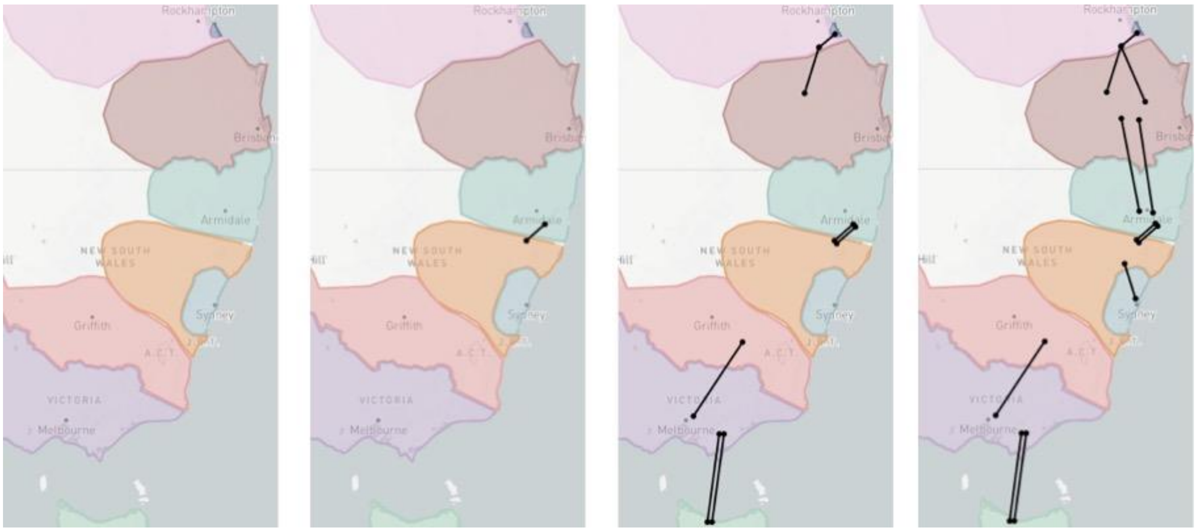


Figure 4.8. LWR/LWWR optimal path (development paths 8 and 13) covering years 2022, 2027, 2032, and 2037 from left to right

4.3 Comparison between deterministic and stochastic planning

In Section 3.4.1 the results for the 6-week stochastic case were presented. The use of the stochastic model resulted in an optimal expected total (operation costs and investment in transmission assets) cost of $22.94 billion over the next 20 years as seen in Figure 3.12. The total costs for the different scenarios covered a substantial range, starting at $15.3 billion for scenario 1, going up to $25.13 billion for scenario 12. Figure 3.11 presented the optimal stochastic investments observed for scenario 1, 9, 15 and 18, which correspond to the original scenarios considered in the ISP 2022, namely Slow, Progressive, Step and Hydrogen Superpower scenarios, respectively.

The cost and regret matrices from the deterministic-based approach are presented in Figure 4.6, obtained by applying steps (i)-(v) described in Section 4.1. For easier interpretation, the numbers have been rounded to the nearest integer. The cost matrix diagonal represents the total cost determined for each scenario's optimal deterministic results during the development path determination process. As a result, the diagonal value for any given scenario (row) is the smallest possible. For example, the diagonal value for scenario 10 is $21.3 billion, which represents the best investment options found for that scenario's conditions. In contrast, the stochastic solution for scenario 10 is $23.59 billion, as it considers the potential scenarios in the scenario tree and results in a compromise solution for all scenarios, which may be more costly than its deterministic counterpart.

After completing steps (vi) and (vii) as described in Section 4.1, the LWR solution for this study can be easily identified. The LWR metric is used to select the development paths found for scenario 8 and scenario 13. It should be noted that if LWWR analysis is extended, the optimal results would be the same in this case. These two scenarios have the same deterministic development path, except for year 2027, where scenario 8 is slow and scenario 13 is progressive. Therefore, both scenarios have the same worst regrets, which occur if the development path is implemented in the system, but scenario 18 (H2 superpower) occurs.

Figure 4.8 shows that the LWR approach only requires one transmission reinforcement in 2022 (CNSW-NNSW Option 6, as specified in ISP 2022), while the stochastic approach requires three reinforcements (CNSW-NNSW Option 6, CNQ-GG Option 1, SQ-CNQ Option 2). At first glance, this might be interpreted as an advantage of the LWR approach since it requires less short-term investment. However, this may not necessarily be accurate when considering the long-term outcomes for the system.

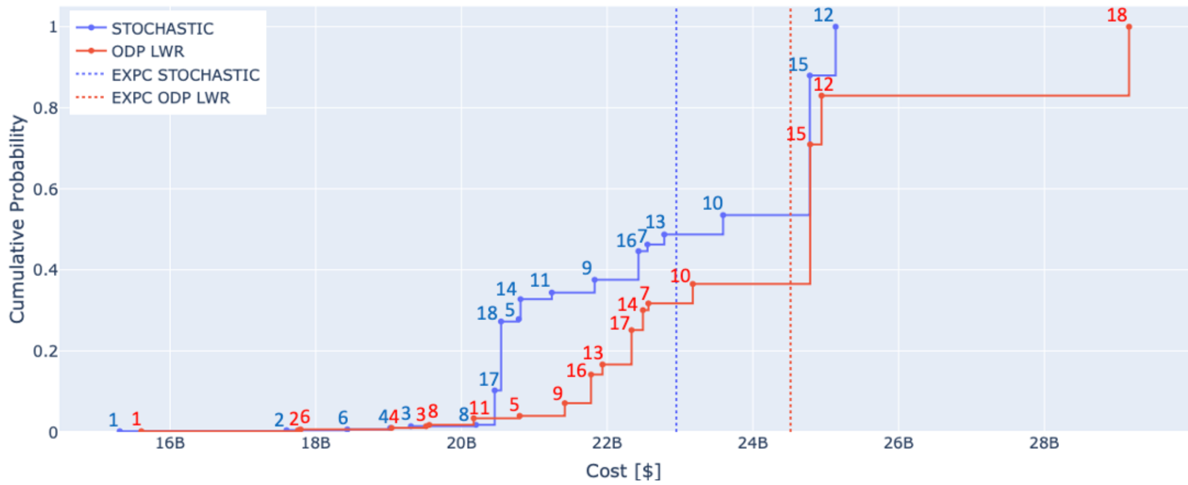


Figure 4.9. Comparison between optimal stochastic results and the LWR optimal development path (ODP)

It can be established that, for this study, the scenario tree depicted in Figure 4.3 provides a more accurate representation of the future than the resulting disaggregated deterministic scenarios. While the deterministic scenarios are derived from the scenario tree, they are considered as independent representations of the future rather than a cohesive perspective. Therefore, the performance of the optimal portfolio identified through the LWR metric (Figure 4.8) should be evaluated within the scenario tree representation of the future. This result is already reflected in Figure 4.6, specifically in the columns related to the costs of considering candidate development paths 8 and 13 across scenarios. Figure 4.9 expands on Figure 3.12 by incorporating the cumulative probability distribution of costs derived from the optimal development path determined by the LWR metric.

It is possible to see that the investment strategy resulting from the LWR approach yields results in which not only the expected total costs of transmission investment and operation are $1.5 billion more expensive, but also the worst performing scenario for the LWR portfolio is $4 billion more expensive than the worst performing scenario using the stochastic approach.

Another interesting comparison that can be conducted to understand the difference between the stochastic and deterministic approaches is to apply the LWR procedure to the development paths found through the stochastic planning approach (see Figure 3.11). This is done by calculating the matrices of costs using the optimal development paths found through the stochastic approach (five different development paths where found) and determining the development path that minimises the worst regret. Figure 4.10 displays the results of this process, indicating that the development path associated with scenarios 15 to 17 minimises the worst regret.

	STOCHASTIC COSTS (B$)																	
	SP1	SP2	SP3	SP4	SP5	SP6	SP7	SP8	SP9	SP10	SP11	SP12	SP13	SP14	SP15	SP16	SP17	SP18
S1	15	15	15	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
S2	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18
S3	19	19	19	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
S4	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19
S5	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21
S6	21	21	21	18	18	18	18	18	19	19	19	19	19	19	19	19	19	18
S7	22	22	22	23	23	23	23	23	23	23	23	23	23	23	23	23	23	64
S8	23	23	23	20	20	20	20	20	20	20	20	20	20	20	20	20	20	60
S9	21	21	21	21	21	21	21	21	22	22	22	22	22	22	22	22	22	22
S10	23	23	23	23	23	23	23	23	24	24	24	24	24	24	23	23	23	24
S11	24	24	24	21	21	21	21	21	21	21	21	21	21	21	21	21	21	20
S12	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	66
S13	25	25	25	23	23	23	23	23	23	23	23	23	23	23	23	23	23	63
S14	26	26	26	23	23	23	23	23	21	21	21	21	21	21	21	21	21	19
S15	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	66
S16	25	25	25	22	22	22	22	22	23	23	23	23	23	23	22	22	22	63
S17	26	26	26	23	23	23	23	23	21	21	21	21	21	21	20	20	20	19
S18	27	27	27	24	24	24	24	24	22	22	22	22	22	22	22	22	22	21

	STOCHASTIC REGRETS (B$)																	
	SP1	SP2	SP3	SP4	SP5	SP6	SP7	SP8	SP9	SP10	SP11	SP12	SP13	SP14	**SP15**	**SP16**	**SP17**	SP18
S1	0.0	0.0	0.0	0.3	0.3	0.3	0.3	0.3	0.7	0.7	0.7	0.7	0.7	0.7	**0.6**	**0.6**	**0.6**	0.7
S2	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.6	0.6	0.6	0.6	0.6	0.6	**0.4**	**0.4**	**0.4**	0.6
S3	0.0	0.0	0.0	0.2	0.2	0.2	0.2	0.2	0.6	0.6	0.6	0.6	0.6	0.6	**0.5**	**0.5**	**0.5**	0.6
S4	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.6	0.6	0.6	0.6	0.6	0.6	**0.4**	**0.4**	**0.4**	0.6
S5	0.0	0.0	0.0	0.2	0.2	0.2	0.2	0.2	0.6	0.6	0.6	0.6	0.6	0.6	**0.5**	**0.5**	**0.5**	0.6
S6	3.3	3.3	3.3	0.5	0.5	0.5	0.5	0.5	0.9	0.9	0.9	0.9	0.9	0.9	**0.8**	**0.8**	**0.8**	0.0
S7	0.0	0.0	0.0	0.2	0.2	0.2	0.2	0.2	0.4	0.4	0.4	0.4	0.4	0.4	**0.2**	**0.2**	**0.2**	41.4
S8	2.8	2.8	2.8	0.0	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.2	0.2	0.2	**0.0**	**0.0**	**0.0**	40.3
S9	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.6	0.6	0.6	0.6	0.6	0.6	**0.4**	**0.4**	**0.4**	0.6
S10	0.0	0.0	0.0	0.2	0.2	0.2	0.2	0.2	0.6	0.6	0.6	0.6	0.6	0.6	**0.5**	**0.5**	**0.5**	0.6
S11	3.3	3.3	3.3	0.5	0.5	0.5	0.5	0.5	0.9	0.9	0.9	0.9	0.9	0.9	**0.8**	**0.8**	**0.8**	0.0
S12	0.0	0.0	0.0	0.2	0.2	0.2	0.2	0.2	0.4	0.4	0.4	0.4	0.4	0.4	**0.2**	**0.2**	**0.2**	41.4
S13	2.8	2.8	2.8	0.0	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.2	0.2	0.2	**0.0**	**0.0**	**0.0**	40.3
S14	6.3	6.3	6.3	3.5	3.5	3.5	3.5	3.5	1.4	1.4	1.4	1.4	1.4	1.4	**1.2**	**1.2**	**1.2**	0.0
S15	0.0	0.0	0.0	0.2	0.2	0.2	0.2	0.2	0.4	0.4	0.4	0.4	0.4	0.4	**0.2**	**0.2**	**0.2**	41.4
S16	2.8	2.8	2.8	0.0	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.2	0.2	0.2	**0.0**	**0.0**	**0.0**	40.3
S17	6.3	6.3	6.3	3.5	3.5	3.5	3.5	3.5	1.4	1.4	1.4	1.4	1.4	1.4	**1.2**	**1.2**	**1.2**	0.0
S18	6.3	6.3	6.3	3.5	3.5	3.5	3.5	3.5	1.4	1.4	1.4	1.4	1.4	1.4	**1.2**	**1.2**	**1.2**	0.0
	6.3	6.3	6.3	3.5	3.5	3.5	3.5	3.5	1.4	1.4	1.4	1.4	1.4	1.4	**1.2**	**1.2**	**1.2**	41.4

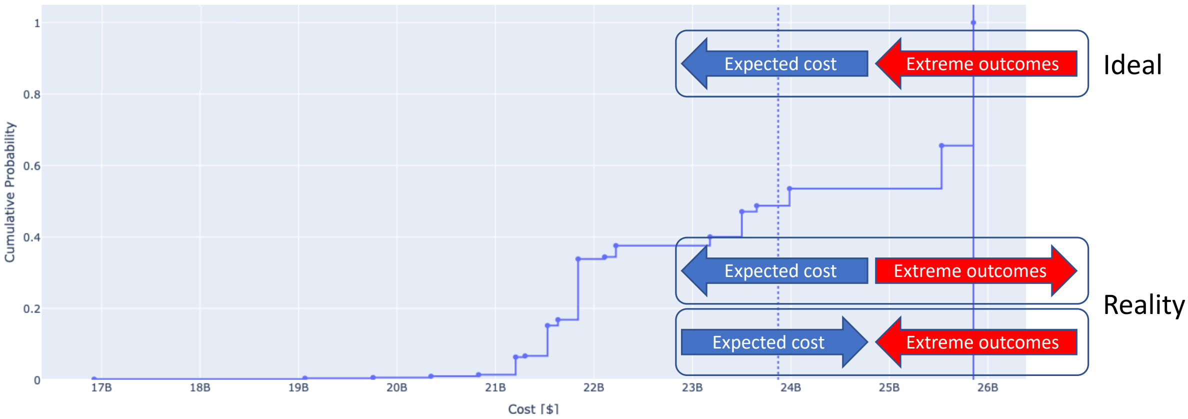
Figure 4.10. LWR calculations based on the use of the optimal development paths for each scenario found through the stochastic

Interestingly, the results demonstrate that the more connected the scenario tree is, the lower the observed regrets will be. Specifically, the regrets for all development paths, except for scenario 18, fall within the range of $1.2 to $6.3 billion. Including scenario 18, the range expands to $1.2 to $41.4 billion. In contrast, the deterministic-based LWR approach, as shown in Figure 4.6, results in regrets ranging from $8.8 to $169.9 billion. This suggests that the stochastic approach, by considering all the available information about the future of the system, can effectively hedge against extremely large regrets.

5 Controlling the risk of a portfolio

The discussions so far have addressed decision making based on a specific value attribute/indicator (e.g. cost or regret) and based on minimisation of expected values (stochastic) or highest values (LWR/LWWR) in uncertain situations. No matter which method is used, decisions will result in a distribution of potential outcomes, which can vary in different scenarios. However, these approaches disregard a full analysis of the resulting risk implications. The decision maker also has little control on the ability to change the risk profile of the approach, being fundamentally risk neutral for stochastic analysis or any assessment based on expected cost and risk-averse for a full LWR [4]. Also, as discussed in [4], LWWR enables risk attitude modulation, but in a way that may not be entirely clear.

In general, for a decision maker it may be desirable to be able to both reduce expected costs while keeping the risk of the resulting portfolio “under control”. As a result, when uncertainty is present, decision-making is inherently linked to a trade-off between future costs and risk. To prevent unacceptable decisions, principles of risk management and expected cost minimisation must be incorporated into the methodology to make decisions.



Error! Reference source not found. depicts, in a general illustrative way, the impact of the attempt to control expected cost and risk: ideally, it would be ideal to be able to select a portfolio capable to push down *both* the expected cost of the portfolio and the worst outcomes (taken as a measure of risk) that could potentially occur as uncertainty unfolds. The reality is that any attempt to reduce the extreme outcomes will introduce the need for additional investment (a “risk hedge”), which in turn will increase the expected cost. Also, any attempt to reduce the expected cost of the portfolio, for instance by investing in cheaper options in the portfolio, will inevitably lead to a poorer performance (higher overall costs) of the portfolio in certain scenarios, otherwise they would have been selected in the original optimal portfolio.

The previous result is valid for a *fixed* set of investment options. Introducing new investment alternatives (in particular, flexible technologies) to the existing portfolio of options could in principle achieve the ideal outcome of reducing both the expected costs and the extreme outcomes at the same time. For instance, let's imagine that a new investment option (let's say a different technology of transmission line) unlocks the same transfer capability as another option that was already selected in the optimal portfolio for all the scenarios, but it is cheaper to build. This option will now be selected, which will reduce the overall expected cost of the portfolio, and in particular will reduce the total cost of the worst outcome, as the new selected option is present in all scenarios.

5.1 Risk management in stochastic planning

To depict the concept of actively addressing the trade-off between costs and risks, one possible approach is to extend the simplified model presented in Figure 3.2 to include the risk component in the objective function of the problem. So far, as shown in Figure 5.1a, the stochastic planning model has been built to search for a set of reinforcements that minimises the expected costs of investment and operation given a representation of future uncertainty (i.e., given a scenario tree).

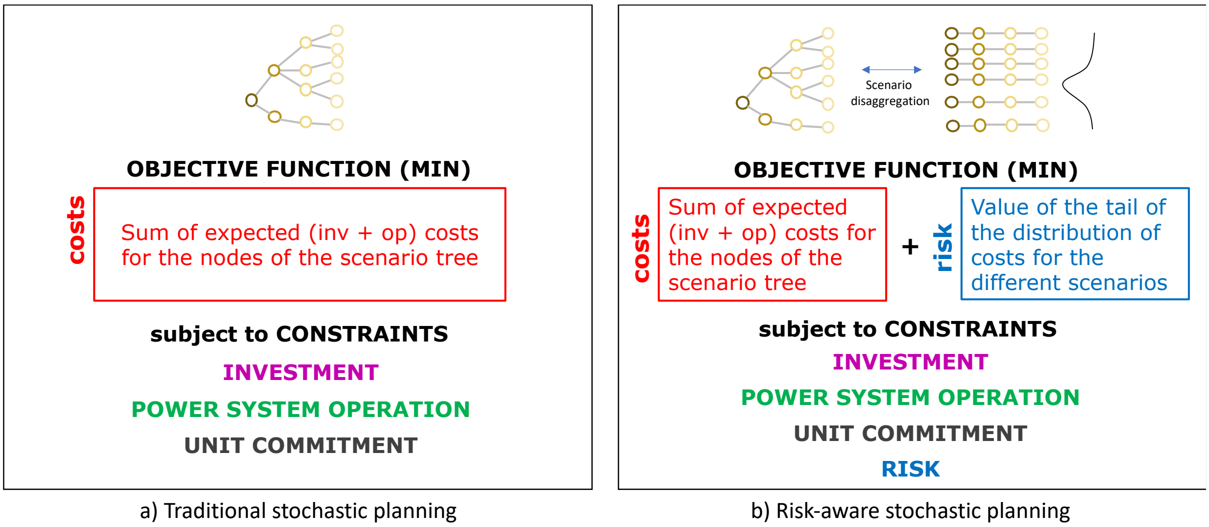


Figure 5.1. Contrast between risk-aware and traditional stochastic planning

Including the assessment of risk in the stochastic planning approach involves keeping track of a metric of the worst performing scenarios and commanding the model to select, for instance, investments that minimise that metric. Such an approach, which focuses on minimising a given risk metric, is fundamentally risk averse. On the other spectrum, of course, there is the minimisation of expected costs, as done so far, which is again fundamentally risk neutral (as it does not model risk). It is intuitive to realise that a hybrid strategy could be to develop an objective function that aims to minimise a combination of the expected costs and the risk metric. Figure 5.1b depicts how this hybrid strategy affects the structure of the original problem. The first task corresponds to vest the model with the capability to track the value of the different scenarios, which requires to model the disaggregation of the original scenario tree into the individual scenarios modeling a full path between the present and the end of the horizon. Keeping everything else equal, these auxiliary variables that keep track of the cost of the disaggregated scenarios are used to represent the metric used to assess risk, which in turn is included alongside the cost minimisation objective. The use of a risk metric usually also involves the need to include additional constraints in the optimisation model (see also [133] for general discussions on stochastic modelling and risk analysis).

The structure of the model introduced in Figure 5.1b is, however, not complete or the most general yet. The reality is that the planner would like to balance out its position on risk. A more risk-averse approach will prefer to favour the minimisation of risk at the expense of increasing the expected total cost of the system, whereas a risk neutral planner will just focus on minimising the expected cost, as it is neutral about the risk of the portfolio. This stance on risk could therefore be parametrised in the model using a linear combination of the two objectives via the introduction of the risk parameter β.

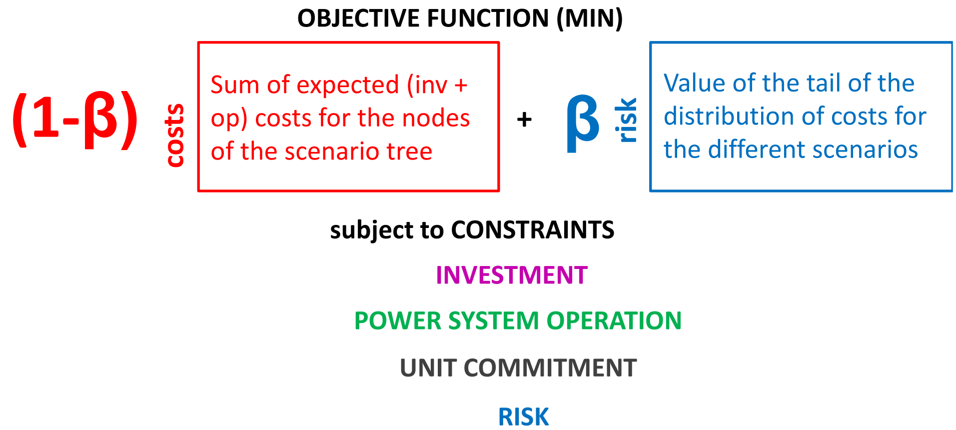


Figure 5.2. Parametrisation of the risk appetite of the planner

Figure 5.2 shows how the parameter β is included in our general **risk-aware stochastic planning model**. It takes values in the range 0 to 1, whose extremes yield the following risk appetites:

- β = 0 corresponds to a risk-neutral assessment (expected cost minimisation only)
- β = 1 corresponds to a risk-averse assessment (e.g., risk minimisation only)

Seen with these new lenses, all the results relative to the stochastic planning model presented in earlier sections of this report have considered a risk neutral position, that is, β = 0. The objective of the following sections is to analyse the impact of making decision while modulating the risk. A natural analysis that can be conducted in the context of the risk-aware framework is to map the results found for several values of the β parameter. This will be referred to as parametric risk assessment, and it will yield the so-called "efficient frontier", which is depicted in Figure 5.3.

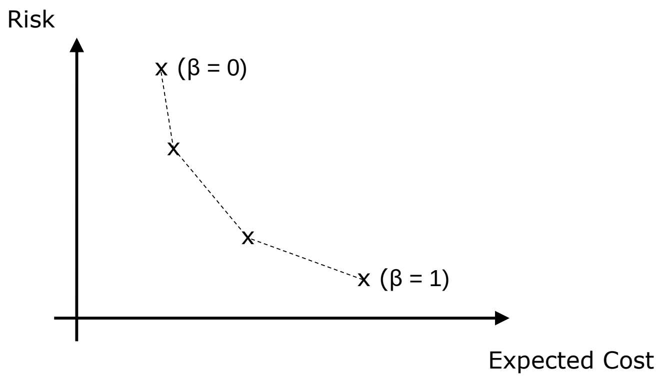


Figure 5.3. Efficient frontier of the parametric risk assessment

An efficient point in the frontier represents the optimal balance of cost and risk for a given risk appetite (parameter β). It is a combination of expected cost and risk that cannot be improved upon by simultaneously reducing both cost and risk. Therefore, choosing a solution with a lower expected cost than an efficient point means accepting a higher risk, and vice versa. This study is fundamental to define the optimal portfolio for the system, as it clearly informs about the premium that must be paid from the perspective of expected costs to achieve a reduction in the risk of the portfolio.

There is one last element to be discussed before introducing the results of the studies conducted on the 32-node instance studied in this report: the risk metrics.

5.2 Risk metrics

Thus far we have discussed the approach that is taken in stochastic planning to control the risk of the portfolio. We have described risk with concepts like “the worst performing scenarios”, “the worst outcomes”, “the value of the tail of the distribution”, so we should clarify the definition of risk metric and describe the one that will be used in the context of this report.

A risk metric is the quantification of a potential loss associated to a portfolio of assets or, in general, an investment strategy. It provides a quantitative way to evaluate the possible downsides of an investment, enabling the planner of a transmission network to make informed decisions about the allocation of resources and the management of risk.

For example, [133] presents different risk metrics used in the context of generic stochastic modelling:

- **Variance** is a statistical measure of the dispersion of a set of data points around their mean. High variance indicates that the returns are widely spread out and that there is a large degree of uncertainty in the portfolio's returns. In other words, a high variance indicates a higher level of risk: the more spread there is, the more likely it is there will be a particularly bad outcome.

- **Shortfall probability** is a measure that represents the likelihood of the total costs of a portfolio that will be over a target or threshold value. It is a measure of the risk that an investment will not perform as expected or that a system will become more expensive than a given value.
- **Expected shortage** is strictly connected to the shortfall probability. For a given predetermined cost level, the expected shortage measures the expected value of those scenarios performing worse that than the target value.
- **Value-at-Risk (VaR)** is a risk metric largely used in portfolio management. Contrary to the shortfall probability and the expected shortage metrics that are calculated based on a predefined target value of cost, the VaR is defined as the value above which a percentage of the costs of the distribution are expected to fall, given a predefined confidence level.
- **Conditional Value-at-Risk (CVaR)** is defined as the expected value of all the values of the distribution that are above the target probability (or confidence level). Using the definitions of VaR, CVaR corresponds to the expected value of all the values that are above and including the VaR.

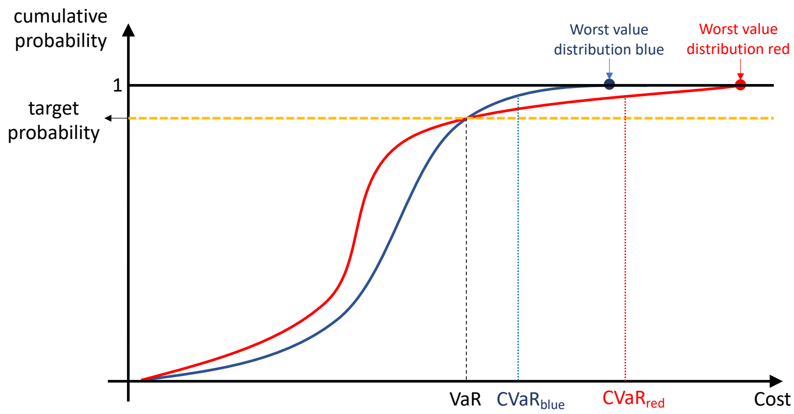


Figure 5.4. VaR and CVaR for two different distributions

In general, VaR and CVaR are the most widespread metrics for risk analysis. There are several reasons for this, both from the perspective of the properties of the information that the metrics provide or require and also from the perspective of their implementation. The main reason for their suitability is the fact that the planner has only to define a confidence interval to study the risk, rather than determining a threshold value for the cost (as it is needed for the shortfall probability and the expected shortage). The variance metric is not as strong for these studies, as it factors in the dispersion of all the distribution rather than focusing on the bad outcomes.

Figure 5.4 also illustrates why CVaR is often the preferred risk measure to manage risk in planning decision. In simple terms, VaR provides information about the cost when the worst-case scenarios (as defined by the selected target probability) start to occur, while CVaR informs what the expected cost of those worst-case scenarios is and provides information about their distribution. As seen in the figure, both distributions have the same VaR, but the metric is blind to the worst outcomes experienced in the distribution depicted in red. CVaR is more useful for identifying scenarios with low probability but high costs, which can significantly increase the average cost of the worst-case scenarios. This makes CVaR an attractive risk measure for transmission expansion planning problems, where these types of scenarios can occur, and also where *resilience* can become a relevant phenomenon to study to select the investment options that better hedge the system against high-impact low-probability events. On top of these features, CVaR also has better mathematical properties that lead to a more tractable problem than the one resulting from the use of VaR, because the latter requires the use of additional binary decision variables for its definition.

5.3 Case study applications

The use of risk metrics generally leads to additional computational burden, as now the investment and operation decision are made looking also at the shape of the distribution of costs for the scenarios. In order to produce enough studies to understand the effect of this approach on the investment decisions, we use the lighter version of the 32-node tree, which uses only *one* week to represent operation in each node (ISP22_32_1W). All the studies we conduct in this report use CVaR-95%, which means that the risk metric will be the expected value of the 5% worst performing scenarios. Essentially, the cost distribution for the case where β equals 0 has already been covered for case ISP22_32_1W in the results presented in Figure 3.13. The label for the risk neutral case is CVAR_beta0.00_32N_1W, whereas the risk averse case is labelled CVAR_beta1.00_32N_1W. Figure 5.5 presents the resulting distribution for the two extremes of the parametric analysis, also highlighting the CVaR (solid line) and expected cost (EXPC, dotted line) for each distribution. In the particular cases under analysis, the 95% threshold approximately corresponds to the last three markers in each distribution in the figure. It is evident that how minimising only the risk achieves the objective of limiting the cost of the worst scenarios (CVaR reduces \$1.87B), but it comes at the cost of a substantially higher expected cost (extra \$1.86B).

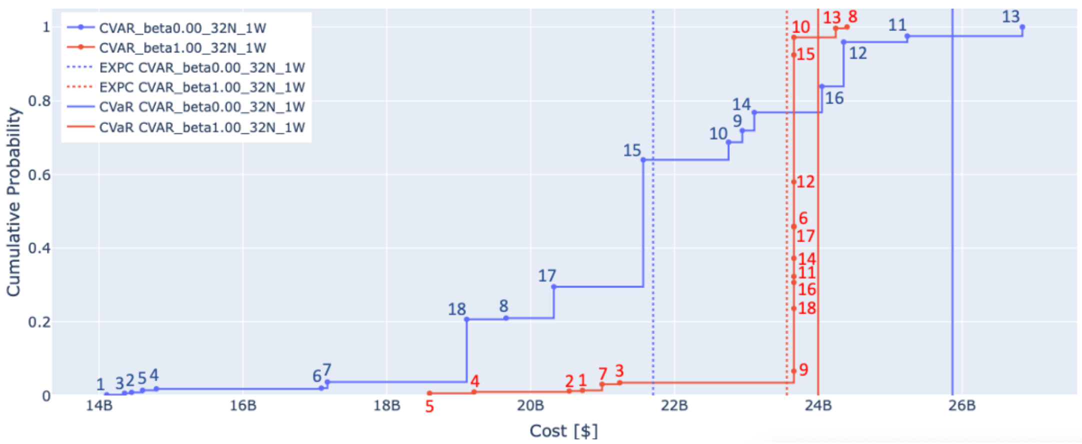


Figure 5.5. Cumulative distributions for the 1-week case for the risk neutral and risk averse case

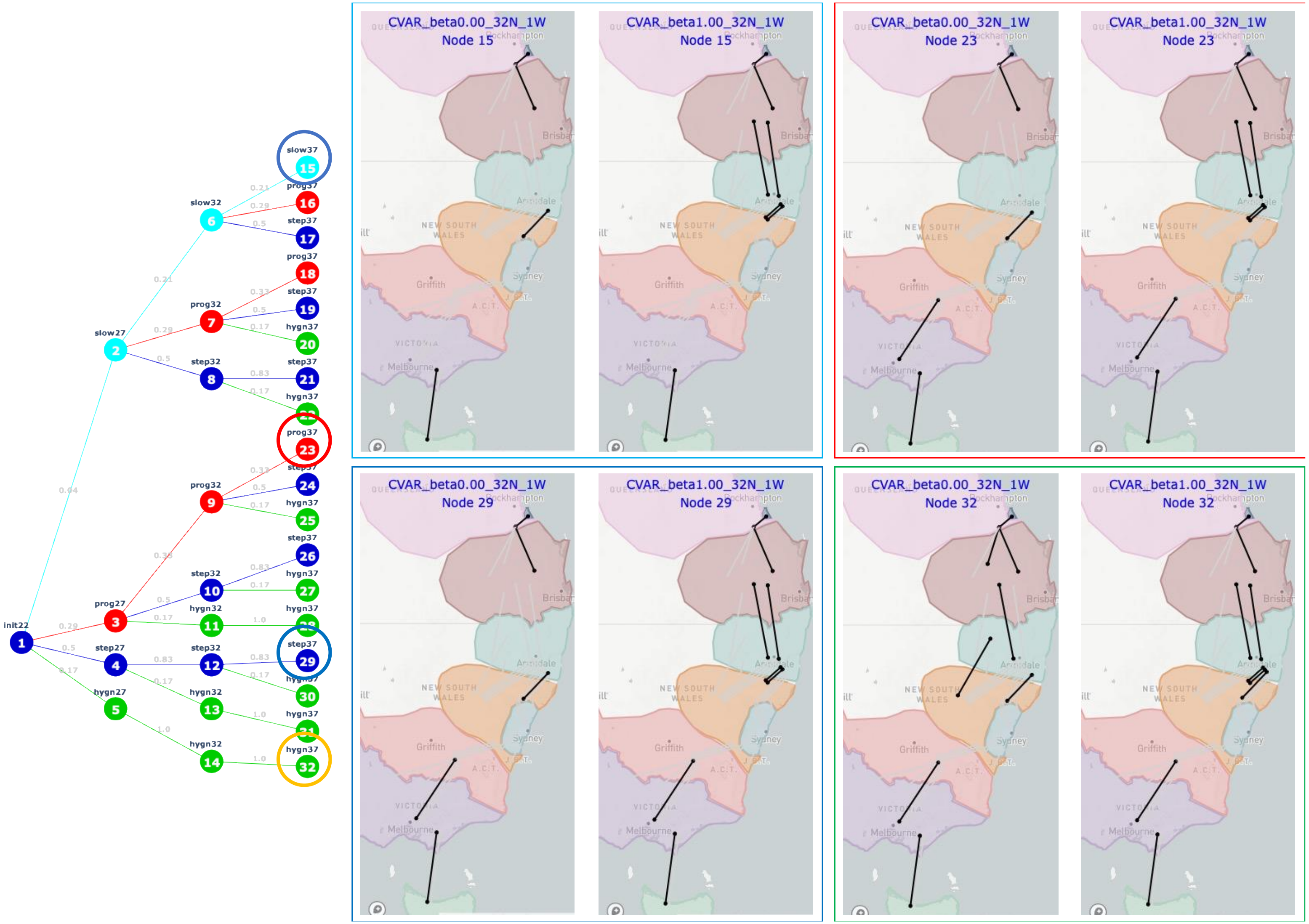


Figure 5.6. Comparison between the investment results for the risk neutral and risk averse 1-week cases for nodes 15, 23 29 and 32 (see labels in blue in each map).

Figure 5.6 shows the comparison across nodes 15, 23 29 and 32 (leaf nodes in the scenarios representing the original scenarios used in the ISP 2022) in the scenario tree for the two risk cases under consideration. The straightforward conclusion is that higher levels of risk aversion lead to a higher reinforcement of the network. This approach results in a substantial increase in the total costs of several scenarios, but also enables the reduction of the costs associated to the most expensive scenarios, which translates in a very narrow distribution of costs for the different scenarios.

The essence of any transmission planning methodology corresponds to the identification of the investment options that need to be proceeded today (or within a certain time horizon before a new assessment is made) to achieve their deployment in the nearest future possible (earliest in service date, to use National Grid ESO terminology). To that end, Figure 5.7 displays the set of transmission investments that are proceeded in year 2022, which are the ones that become active (are physically deployed) in year 2027 (nodes 2, 3, 4 and 5, showing only node 3 in the figure as the results are the same due to the fact that they share the same parent node 1).

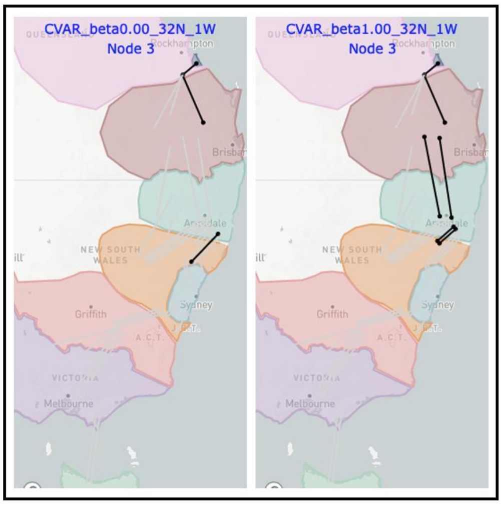


Figure 5.7. Investments recommended in year 2022 for the risk-neutral (left) and risk-averse (right) approaches.

It is possible to see that the risk averse case triggers the construction of two links between SQ and NNSW (NNSW–SQ Option 1 and 2) and two links between NNSW and CNSW (CNSW-NNSW Option 6 and 6A), which hints that enabling the corridor between SQ and CNSW is a hedge against extremely negative scenarios that might appear in the future[9].

By solving the same problem for a CVaR-95% with β = [0.25, 0.5, 0.75] it is possible to see a good approximation of what the efficient frontier looks like. This result is presented in Figure 5.8, which highlights that this particular case lends itself for a relatively easy decision between risk and expected cost. The nature of the frontier clearly shows the initial trade-off described

[9] Under the simplifying assumption of one typical week operational representation.

before, whereby in order to decrease the risk by $1.87B the expected cost premium would be $1.86B. With the information presented in the figure, it is possible to ascertain that a risk aversion associated to a β = 0.75 may represent a much better trade-off between expected costs and risk, because the risk is reduced almost as much as β = 1.00 ($1.868B), but the premium to be paid in terms of expected cost is much smaller ($0.3B). Potentially, by exploring the frontier further, a better trade-off can be found.

The key message from the efficient frontier analysis is embedded in the ratio between risk reduction and the premium to be paid. This means that for each scenario tree that may be studied, any sensitivity on probabilities, etc., will require the full assessment of the efficient frontier to determine the best trade-off for that case.

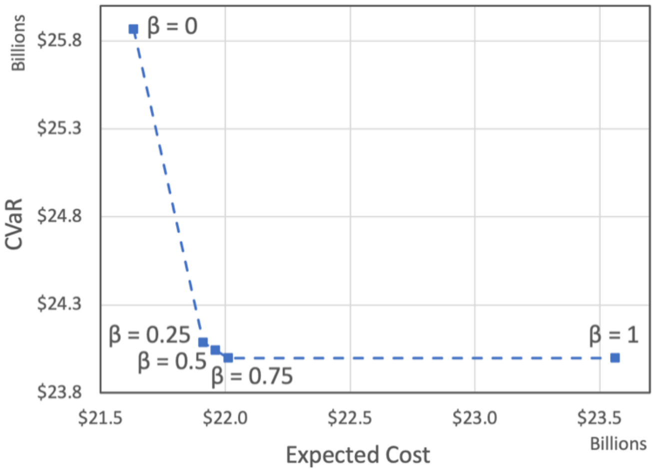


Figure 5.8. Efficient frontier for the case ISP22_32N_1W with CVaR-95% as risk metric

Extending Figure 5.7 using this larger range of risk parameters, it is possible to identify what sets of reinforcements are proceeded in year 2022 (active in nodes 2 to 5, year 2027) to cope with progressive a higher aversion to risk, as seen in Figure 5.9.

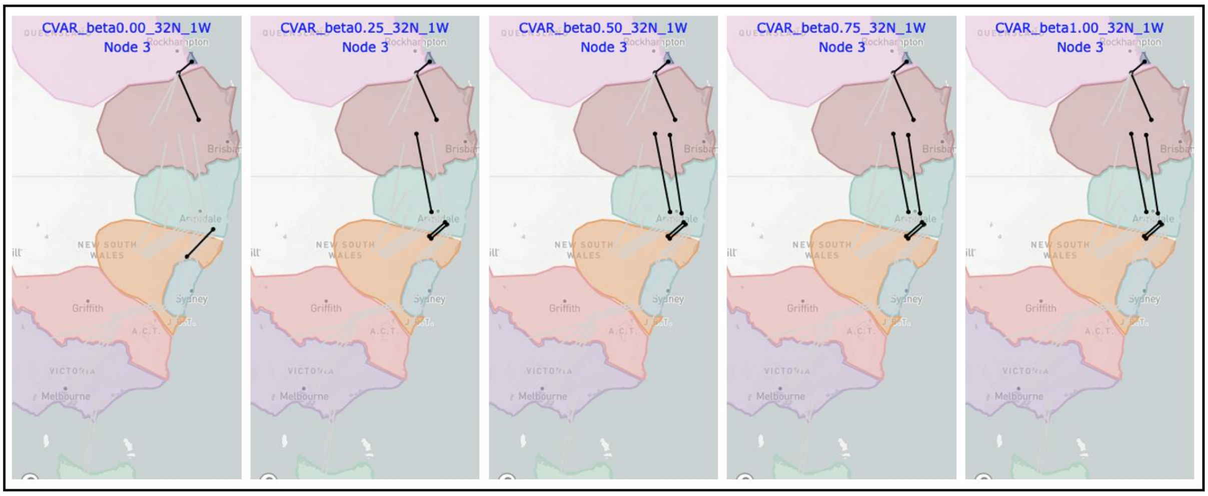


Figure 5.9. Reinforcements proceeded in year 2022 (active in 2027) depending on the level of risk aversion

It can be seen that there only two reinforcements that are progressed independent of the risk aversion level: CNQ-GG Option 1, SQ-CNQ Option 2. The risk neutral approach also considers increasing transmission capacity in NSW using CNSW-NNSW Option 7; however, as the risk aversion increases this transmission option is replaced by two reinforcements: CNSW-NNSW Option 6 and CNSW-NNSW Option 6A. The boundary capacity between NSW and QLD also is key to address higher risk aversions: a risk neutral approach does not observe the deployment of additional capacity in that boundary, but as risk aversion increases, NNSW–SQ Option 1 is build for β = 0.25 and expanded to NNSW–SQ Option 2 when the risk aversion is β = 0.5.

Table 5.1. Investment options proceeded in 2022 for different levels of risk aversion

Line	Line ID	Region A	Region B	Transfer limit (MW)		Investment Cost (M$/MW)
				A to B	B to A	
NNSW–SQ Option 1	**18**	**NNSW**	**SQ**	**910**	**1080**	**1.16**
NNSW–SQ Option 2	**19**	**NNSW**	**SQ**	**550**	**800**	**0.48**
CNSW-NNSW Option 6	**27**	**CNSW**	**NNSW**	**2190**	**1800**	**0.77**
CNSW-NNSW Option 6A	**28**	**CNSW**	**NNSW**	**880**	**1270**	**0.18**
CNSW-NNSW Option 7	**30**	**CNSW**	**NNSW**	**1470**	**1590**	**0.56**

Table 5.1 displays the techno-economic characteristics of the transmission options that may or may not be proceeded in 2022 depending on the risk aversion level. By inspecting the transmission options presented in the table below, we can observe how the investment rules across the set of investments options complicate the selection of the optimal portfolio. For instance, when reinforcing the boundary between NSW and QLD the model is forced to deploy NNSW–SQ Option 1 first, even when NNSW–SQ Option 2 is more cost-effective, as NNSW–SQ Option 2 must follow NNSW–SQ Option 1. Something similar occurs for the boundary between CNSW and NNSW, where CNSW-NNSW Option 6 and CNSW-NNSW Option 7 are mutually exclusive, so to increase boundary capability beyond the capacity of CNSW-NNSW Option 7, the model switches to CNSW-NNSW Option 6 and combines it with CNSW-NNSW Option 6A.

5.3.1 The role of storage in risk-aware planning

Adding the possibility to co-optimise storage along with transmission lines showed marginal benefits in the case studied in section 3.4.3 due to the existence of already a very large amount of storage capacity in the system as planned from the ISP. When including a risk metric in the objective function, additional storage capacity is selected to enable the system to further decrease the investment risk.

To demonstrate the effect of potential additional storage capacity that some extent of risk-aversion could create (on top of the battery storage capacity planned in the ISP), we focus the attention on the *fully* risk averse case (β = 1.00).

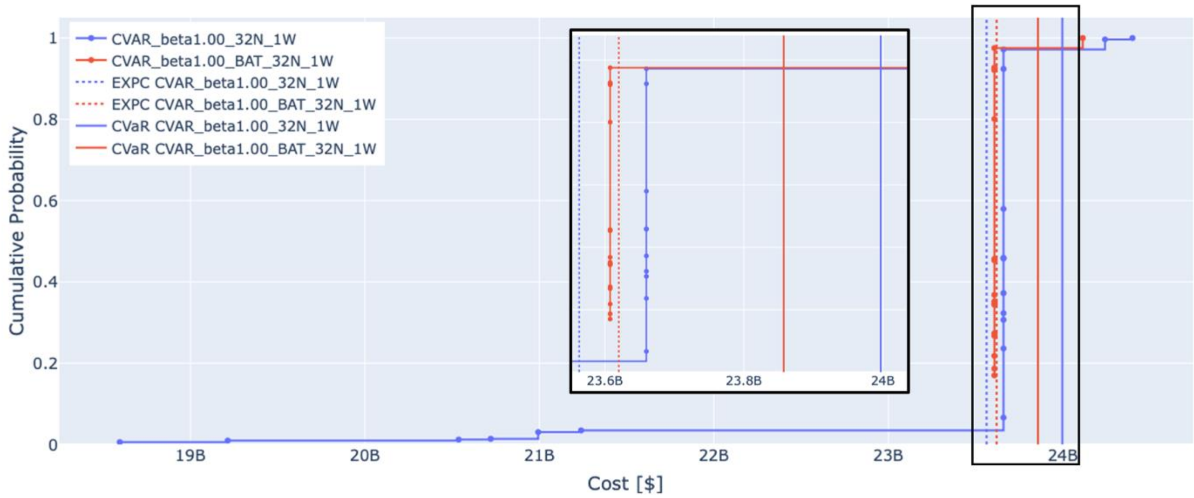


Figure 5.10. Cumulative distributions for the risk-averse approach for the cases with and without battery co-optimisation

Figure 5.10 depicts how the inclusion of flexible investment options like BESS enable the model to find a solution with even a lower CVaR-95%. The reduction in the risk of the portfolio is close to \$140 million, at a premium of additional expected cost of close to \$57 million.

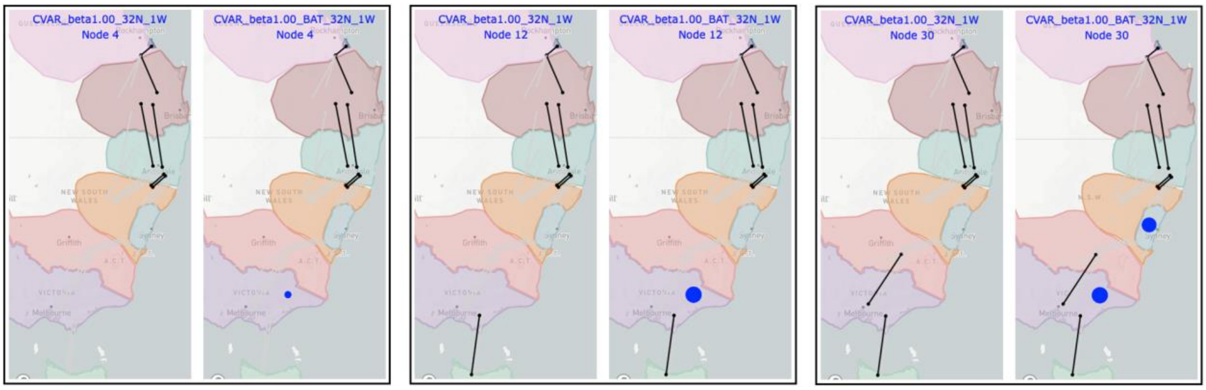


Figure 5.11. Impact on the investment results of considering BESS as additional investment candidates

The impact on the investment options selected to achieve the lowest risk possible is shown in Figure 5.11. Three nodes are selected for years 2027, 2032 and 2037, associated to scenario 16 in the scenario tree: node 4 which corresponds to the step scenario in year 2027, then node 12, which corresponds to year 2032, also representing step scenario conditions. Finally node 30, which describes the system by 2037 under the hydrogen superpower scenario. The amount of additional storage that is built starts with around 150 MW in Victoria in 2027, which then grows to approximately 950 MW by 2032, and 800 MW in the Sydney, Newcastle and Wollongong region in year 2037. It is worth highlighting that storage is substantially cheaper by year 2037, with its investment cost being around 50% of the costs observed today. Figure 5.11 clearly shows that storage is not able to defer or avoid transmission investment, as the transmission portfolio is the same as the one observed for the case without storage investment options. The additional storage is able to accommodate even more of the renewable energy seen at mid-day, further reducing the operation costs in certain periods of the day. These features of storage can help enhance the performance of the system in the most expensive scenarios, thus further reducing risk, as is the objective of the fully risk-averse objective function.

The overall effect of including flexible investment options like additional BESS in the investment set is depicted in Figure 5.12. It is clear that the new portfolio of options both reduces the risk and/or the expected costs for all risk aversion levels, which is translated into an efficient frontier that has been displaced down and to the left, which effectively allows the risk-constrained problem to find portfolios with less risk and less expected costs. For instance, take the case where the risk parameter is set to 0.75. By considering additional investment in batteries we observe how the model is able to find a portfolio that reduces the expected cost in close to \$105 million and the CVaR in ca. \$140 million.

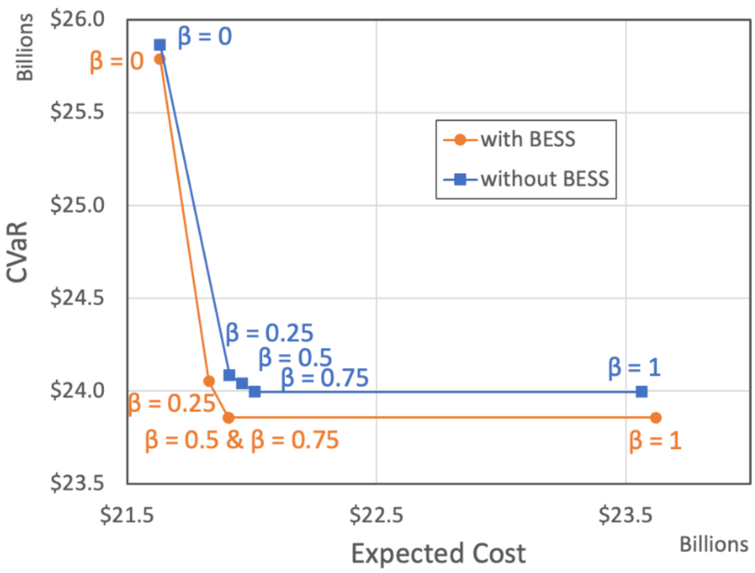


Figure 5.12. Efficient frontier for the case ISP22_32N_1W with and without investment in additional BESS investment using CVaR-95% as risk metric

6 Methodological approaches to incorporate resilience analysis in stochastic planning of power systems.

Extreme events, particularly those related to weather, have caused substantial economic damages to power grids worldwide. As extreme weather events become more frequent and severe, there is an urgent need for a comprehensive understanding of their impact on power system infrastructure to develop strategies that minimise negative effects. In this context, power system resilience has gained significant attention from researchers and policymakers alike, as it is crucial for countries to better comprehend the events, their impacts on grid operations, and the solutions required to enhance the resilience of power systems.

Power system resilience refers to the capacity of a system to endure high impact, low probability events (HILP), recover quickly, and adapt its strategies and resources to mitigate similar events in the future. Over the past ten years various frameworks, methodologies, and measures that have been proposed in the literature to improve power system resilience. These include stochastic optimisation approaches, hardening existing infrastructure, and considering risk aversion in network design and operation.

This section aims to provide an overview of the challenges and potential solutions associated with investments to increase power system resilience. However, it is important to note that the current section will not delve into the seminal aspects of resilience in power systems, as these are thoroughly discussed in recent literature (see section 2.2). Instead, the focus is put on the methodologies to determine what new transmission infrastructure can enhance power system resilience under uncertainty to effectively mitigate the consequences of extreme events on grid operations. As a matter of fact, we propose here three different approaches to deal with resilience in stochastic power system planning. Several case study applications are presented to demonstrate the effects of planning approaches proposed here. These studies are conducted on the same instances studied in the previous sections of this report.

At the end of the section the work conducted in collaboration with EPRI is also presented, which further discusses how to model and select extreme events and disruptive hazards and their effects, and how to incorporate them into capacity planning models. The approach includes hazard-driven load changes, deratings and shutdowns of assets, potential damages and risks to the grid and outside parties, hardening options to mitigate the impacts, and the costs and operational implications associated with implementing these measures.

6.1 Representing extreme events in stochastic power system planning

The mechanics of input data management for resilience studies play a crucial role in accurately representing the uncertainties associated with extreme events. These mechanics are specifically tailored to the structure of the stochastic representation using a scenario tree, which offers important degrees of flexibility in modeling extreme events and their likelihood. This section aims to explore two potential approaches that could be employed effectively to incorporate HILP events in investment decision-making under uncertainty.

The first approach, which will be referred to as *Approach 1*, involves taking advantage of the structure of representative periods (the case of the studies conducted in this report, representative weeks) used to describe system conditions, incorporating *new* representative weeks into the analysis. These weeks would be chosen to represent the extreme operational conditions in a given node or nodes, and the corresponding representative periods would be weighted according to the likelihood of the event occurring. The input data for that week would then be modified to reflect the specific characteristics of the event, such as changes in demand, renewable energy availability, or system architecture.

The justification behind this approach is depicted in Figure 6.1. Let's assume that the planner wants to consider a specific branch in the original scenario tree and model an extreme event in one of the nodes of the tree. In this example, the extreme event is modelled in node 3 as a new representative period additional to the original representation of operation, resulting in a new node, labelled node 3'. The planner then can represent the likelihood of transiting from node 1 to node 3' with a given low probability, which in this case is assumed to be 0.001. This results in a new scenario tree with a copy of the branch that includes node 3, which now includes node 3'.

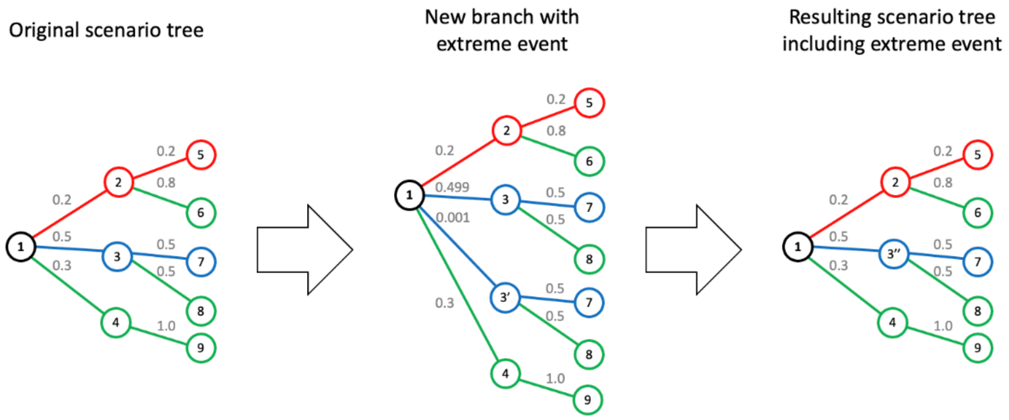


Figure 6.1. Describing extreme events by adding new representative periods within a node (approach 1)

The new branch is essentially the same as the original branch, except from the additional representative week discribing the extreme event. Therefore, the original branch and the new branch can be overlapped, resulting in a new node labelled node 3'', which now includes the representative period describing the extreme event, but is now weighted within node 3'' using the probability of transition between node 1 and node 3'. In summary, the extreme event is added to the original node 3 using a weight that reflects how unlikely it is that such operational condition will occur in the period represented by node 3.

The second approach, which will be referred to as *Approach 2*, involves adding a totally new branch to the scenario tree, which is kept as an independent path into the future. This branch would also model the events by adding additional weeks of operation to capture their effects. However, this approach would also give the planner the ability to describe new scenarios resulting from the event's occurrence, as seen in Figure 6.2. By incorporating these additional scenarios, the planner can understand the potential outcomes of high impact low probability events that may involve drastic changes in the future of the system. Also, this approach enables to identify how the extreme events drive specific transmission investments within the branch that includes the extreme event(s), as opposed to the investment decisions made in the original tree. Further discussions are also reported in Appendix D based on EPRI's work.

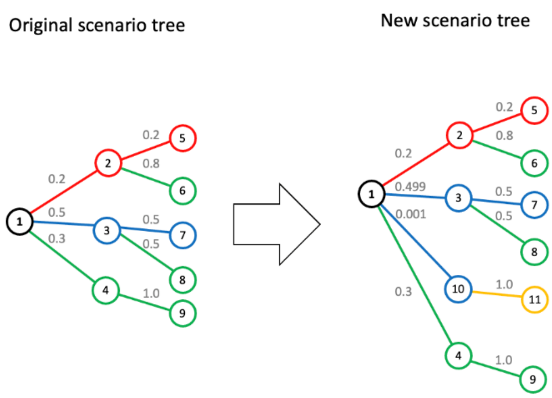


Figure 6.2. Describing extreme events by adding new scenarios to the scenario tree (approach 2)

6.2 Methodologies to include resilience consideration in stochastic power system planning

This section describes three methodologies we propose to study the effect of extreme events in power system planning. The methodologies are discussed from the perspective of expansion planning under uncertainty considering transmission investment options only, but their principles can be applied to any set of investment decisions (e.g., transmission and storage expansion planning).

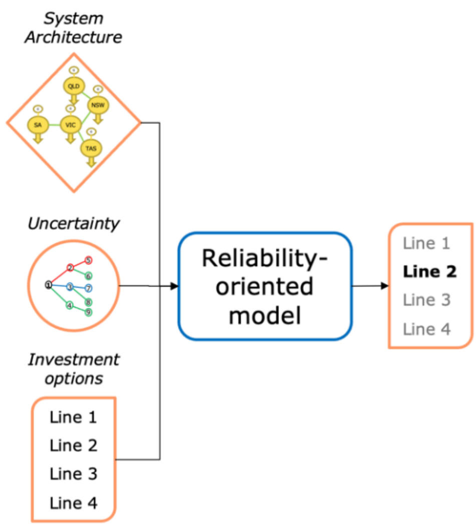


Figure 6.3. General reliability-oriented planning framework

The methodologies are built as an extension to what we could name *"reliability-oriented"*[10] *framework* presented in Figure 6.3, which is the one introduced and used in Section 3 and is the foundation of all the studies conducted throughout this work. The reliability-oriented framework takes three main inputs, namely, the architecture of the system, the description of the system's evolution through a scenario tree, and a set of investment options. These elements are used to populate the stochastic model that is then used to select the investment options that minimise the total expected costs of investing in new assets and operating the system across the conditions described in the scenario tree.

6.2.1 Methodology 1: Risk-averse planning for resilience enhancement

Given the uncertainty around what type of high impact low probability (HILP) events may occur in a system, this methodological approach is proposed to identify a more robust investment portfolio that could in principle behave better under extreme conditions. This approach focuses on selecting a risk-averse portfolio using a reliability-oriented model and the existing representation of uncertainty, by including a risk metric parametrised to indeed identify a more risk-averse portfolio, as described in Section 5. A risk-averse portfolio is more likely to be naturally hedged against extreme events since the planner is likely to prioritise building additional assets to mitigate the risk of operation conditions that may result in very high costs (from the modelled scenarios, and so, indirectly and intuitively, for unknown, extreme events and scenarios too).

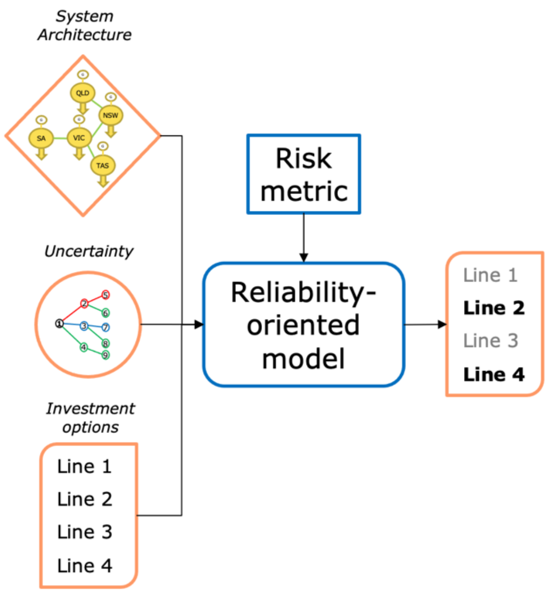


Figure 6.4. Extension of the reliability-oriented planning approach to hedge against extreme conditions (methodology 1)

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[10] The reliability-oriented model refers to the risk-neutral (see section 5) expansion planning model that was introduced in section 3, where reliability-related constraints are represented to guarantee that generation mix is both adequate and the operation is secure.

The effectiveness of the risk-averse portfolio compared to the risk-neutral one can then be tested by recreating operational conditions describing a given HILP event and contrasting the performance of both transmission plans. The resilience of each portfolio can be measured using a bespoke resilience metric, and the reliability value of the risk-averse portfolio can be determined. By using this approach, the planner can identify a more robust investment portfolio that can better handle HILP events and improve the overall reliability of the system.

6.2.2 Methodology 2: Resilience-aware stochastic power system planning

This methodology is the natural step towards finding resilience-focused portfolio after the elements presented in methodology 1. In this case, the objective is to represent the different HILP events under consideration in the description of the future evolution of the system, which naturally involves the definition of a resilience-oriented scenario tree. The tree is modified following the approaches described in Section 6.1.

Following the representation of methodology 1 presented in Figure 6.4, methodology 2 can be described using the same elements, where the structure of the scenario tree changes, as shown in Figure 6.5. The definition of a new representation of uncertainty that includes HILP events changes leverages the reliability-oriented model to implement a resilience-oriented methodology. Since the underlying model is reliability-oriented, this means that reliability is not overlooked in the proposed methodology as all the constraints and considerations that aim to guarantee reliability are still in place in the model.

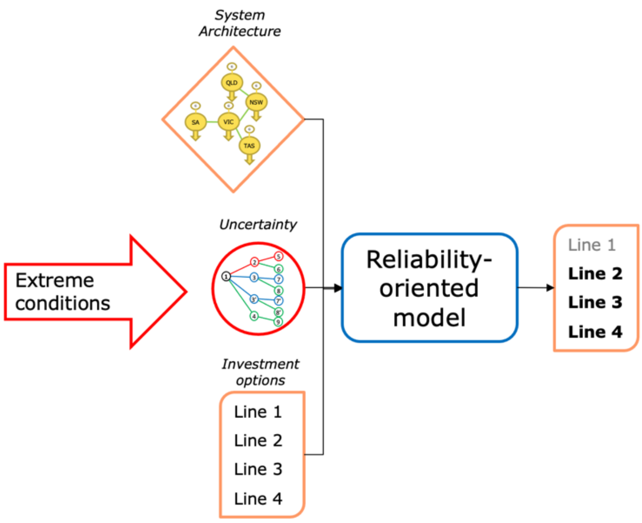

Figure 6.5. Resilience-oriented power system planning (methodology 2)

6.2.3 Methodology 3: Two-step resilience-aware stochastic power system planning

This methodology for developing a resilience-oriented portfolio involves two steps. First, the system is planned for reliability using the reliability-oriented model as presented Figure 6.3.

The resulting optimal investment set is then referred to as the reliability-oriented portfolio, which is provided to the second step of the methodology as part of the system architecture.

Next, the methodology overlays high impact low probability (HILP) scenarios on top of the original scenario tree. This allows for the identification of new optimal plans for the remaining original transmission options that are resilient to HILP events. The resulting investment set is referred to as the resilience-oriented portfolio.

To further refine the resilience-oriented portfolio, a budget limit *may* be included in the reliability-oriented model. This ensures that the selected investments are within the resilience budget allowance. Figure 6.6 describing the methodology can help to visualise the steps involved in developing the reliability-oriented and resilience-oriented portfolios. By following this methodology, system planners can better prepare for and mitigate the potential impacts of HILP events on the system and at the same time, justify the additional assets and what level of investment is needed to provide more resilience.

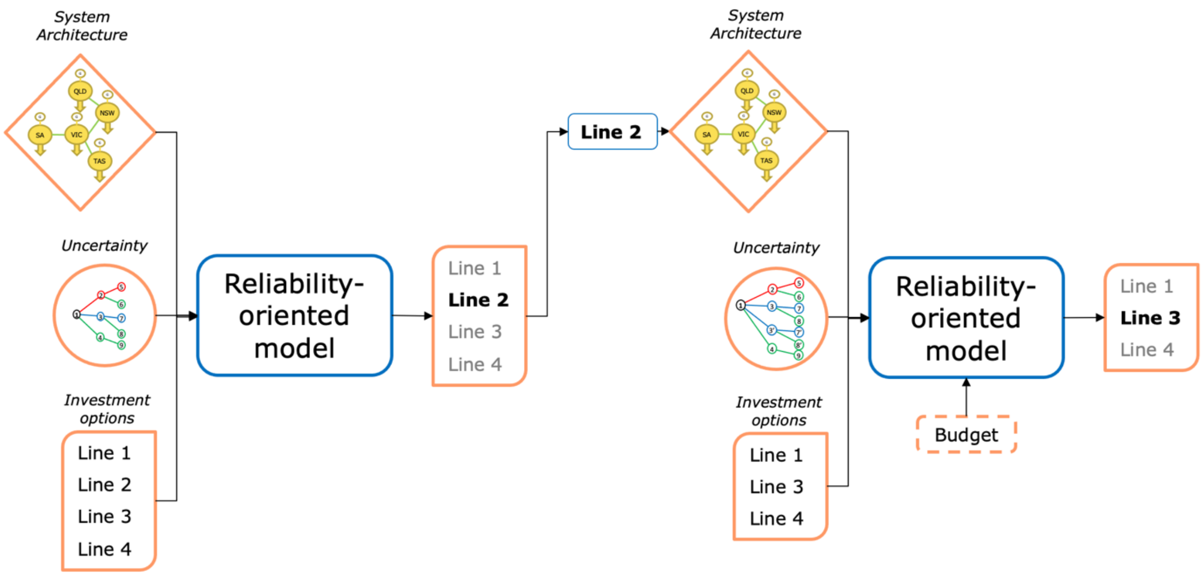

Figure 6.6. Illustration of the two-step methodology to determine resilience-oriented portfolios

6.3 Case study applications

This section seeks to integrate the resilience assessment into the traditional cost-benefit analysis by providing methodological tools and a case study application under the stochastic power system expansion planning framework, focused on methodologies 2 and 3 introduced before. Specifically, it aims to illustrate how the representation of extreme events in transmission expansion planning can contribute to mitigate the potential impact of High-Impact Low-Probability (HILP) events that may occur in the future. The illustrative case study assumes there is an increase in the expected demand and a decrease in the expected output from solar plants in the southern regions of Victoria (VIC), Tasmania (TAS), and South Australia (SA) for a time-window of 10 hours. It should be stressed that this case study is purely notional and illustrative, with the sole aim of creating an opportunity to discuss the proposed methodologies rather than provide any specific result.

The analysis also introduces and explains two concepts related to the occurrence of HILP events: frequency and representativeness. *Frequency* refers to the likelihood of an event occurring over time, while *representativeness* involves including the occurrence of the HILP event throughout the scenario tree.

6.3.1 Extreme event representation

High Impact Low Probability (HILP) events refer to any event that is not usually expected during normal operating conditions, such as extreme weather, exogenous signals like fuel prices, and others. Modelling its occurrence remains still a challenge, and in this methodological analysis, the analysis is done through the addition of representative weeks (approach 1) that characterise the occurrence of the event, together with the concepts of frequency and representativeness, which are later introduced in detail.

6.3.2 Representative weeks

To study the resilience methodologies proposed in this section, the 1-week case study application has been chosen as the base case study. The specific dates utilised for each node are provided in Appendix B: Representation of operation for resilience case study application for reference.

Extreme events, which are used to test the resilience of the system, are also modelled through the previously selected representative weeks. In this case, a specific event occurs within a defined time window and has a particular duration. That event mainly causes unexpected additional demand and lower output of rooftop and large-scale PV generators, leading to a more stressed operation of the system. It is important to highlight that many other parameters can be potentially affected by an extreme event, but only those two have been considered in this illustrative case. As explained in section 6.1 the weights associated to each representative period used to model the operation of the system can be used to characterise the frequency of occurrence of an extreme event, concept which is introduced in the next section. By means of these weights, the optimisation problem can account for the likelihood of an extreme event occurring in the system.

6.3.3 Frequency of a HILP event

The frequency of a HILP event is defined as the probability of the event occurring within a defined time window. The frequency parameter is set as a specific value within the designed framework through the weights used to characterise the representative periods[11]. One of the objectives of this illustrative study is to analyse how changes in the frequency value of an event can impact investment decisions during the transmission expansion planning process.

By incorporating the frequency of HILP events into the planning framework, planners can gain valuable insights into the potential impacts of these events on the power system, allowing for more informed investment decisions. It is important to note that the frequency of HILP events can vary depending on the specific region and time period being analysed. Therefore, when incorporating the frequency of HILP events into the planning process, it is crucial to consider the specific context being studied to accurately reflect the potential impacts of extreme events on the power system.

6.3.4 Representativeness of a HILP event

The stochastic power system expansion planning framework utilises scenarios to represent sets of uncertainties, which may include high impact, low probability events. Including an extreme event in specific futures may lead to different investment decisions compared to when the event is expected to happen in all possible futures. The *representativeness* of an event in the scenario tree refers to its inclusion in different possible futures that the system may face. Properly considering the representativeness of events can be crucial in planning power systems for normal operation as well as for effectively responding to extreme events.

For this case study, representativeness can be categorised as *"zero"*, *"partial"*, or *"full"*. A *"zero"* representativeness means that the HILP event is not considered as part of the uncertainties of the scenario tree, and investment decisions will be made based on the assumption that the event will not occur. A *"partial"* representativeness implies that the event is expected to happen in some, but not all, of the scenarios. In this case, investment decisions will be made considering the possibility of the event occurring in some scenarios but not in others. A *"full"* representativeness means that the event is expected to happen in all scenarios with a specific frequency, and investment decisions will be made based on that assumption. For a better understanding of the representativeness concept, Figure 6.7 provides an illustration of it throughout the scenario tree utilised for this case study application.

[11] For example, let's consider one year consisting of 52 weeks that is being represented using one representative week. If an event is expected to occur once every year, the value of the weight associated to the week with normal operation is 51/52, while the weight assigned to the week that models the occurrence of a HILP event is 1/52.

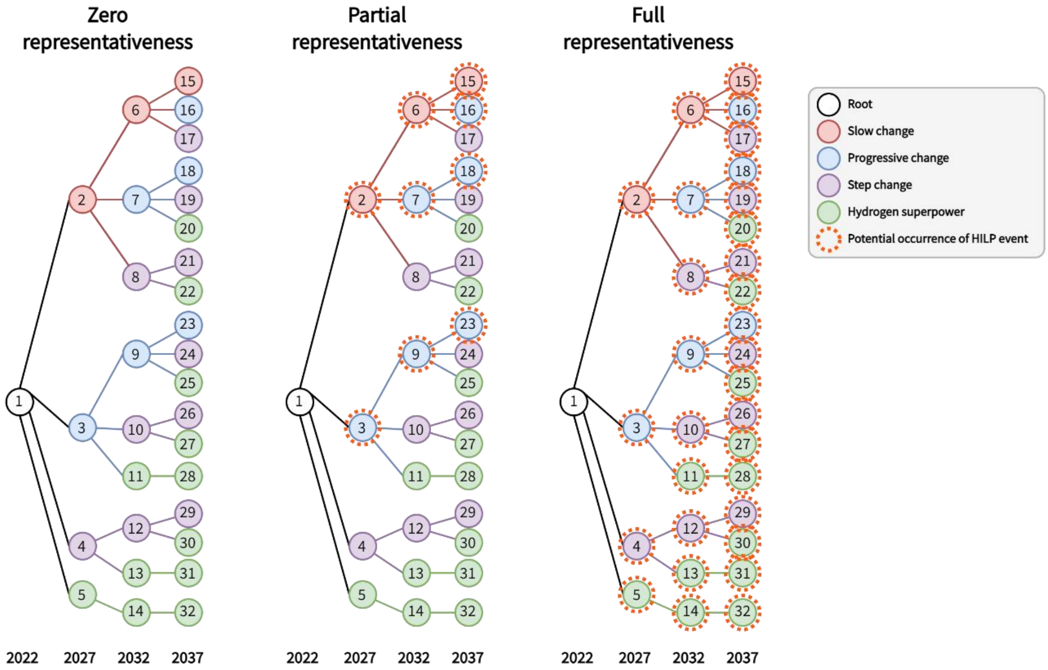

Figure 6.7: Degrees of representativeness throughout the scenario tree used to describe possible futures.

6.3.5 Input data and characterisation of an extreme event

This section introduces the characterisation of the extreme event that was modelled to construct the illustrative study case. Specifically, we show the main methodological steps related to data management that were taken to modify demand and expected output of generators, as well as the impacted areas of the system.

The occurrence of an extreme event can be caused by a variety of variables and events that deviate the system from normal operating conditions. Examples include abnormal weather patterns, higher demand peaks, exogenous signals such as fuel prices, or market events such as early retirement of units.

This illustrative study is focused on the effects of unexpected operating conditions caused by simultaneous higher demand peaks and lower output of rooftop and large-scale PV generators during a hypothetical HILP event. Figure 6.8 and Figure 6.9 illustrate, in a general way, the behaviour of the generators' output and demand during the hypothesised HILP event as compared to a typical normal week. It is important to emphasise that the curves shown are only for illustrative purposes and they do not represent the behaviour of every renewable generator in the system and the demand in affected zones.

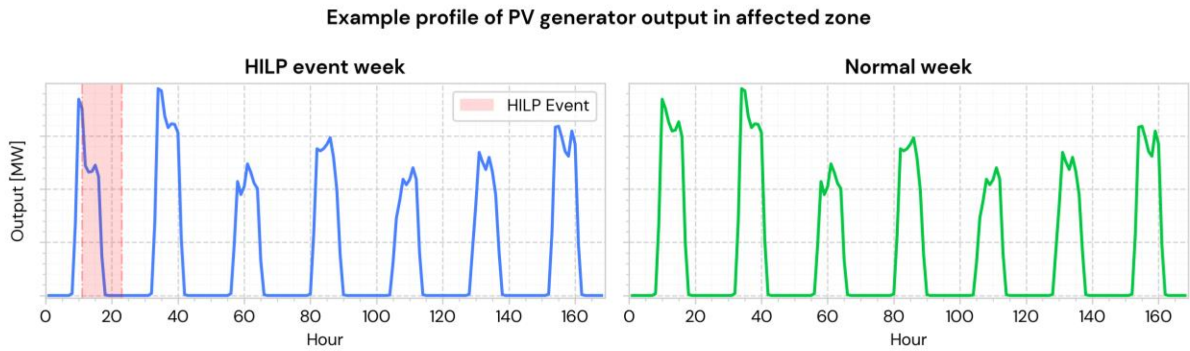

Figure 6.8: Illustrative example of affected generators' output while facing a HILP event and in a normal week.

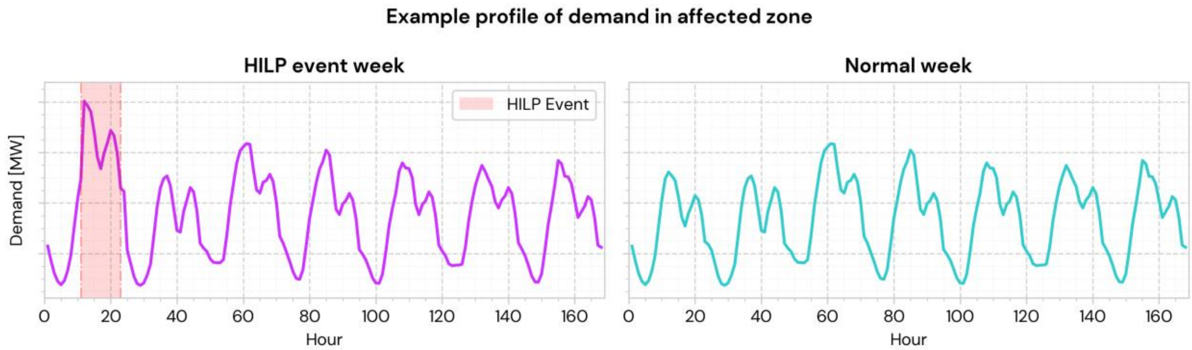

Figure 6.9: Illustrative example of demand profile of affected zones while facing a HILP event and in a normal week.

For this study-case, the HILP event conditions are primarily set for the southern regions of Australia, specifically Victoria, South Australia, and Tasmania, as is highlighted in Figure 6.10.

Figure 6.10: Affected zones of the illustrative study case.

6.3.6 Analysed cases

To analyse and assess the impact of HILP events in the stochastic transmission expansion planning framework, an approach following methodology 2 "Resilience aware stochastic planning"is employed.

To establish a standard of comparison, initially a *"base case"* is created, and relevant base investment portfolios are determined. Subsequently, two cases are constructed to analyse the effect of the frequency HILP events on the investment portfolios obtained. Additionally, cases with partial extreme event representation are executed to evaluate the impact of event representation in the scenario tree.

Table 6.1 summarises the five case study applications under analysis, outlining the specific characteristics of each study, including whether or not the occurrence of the HILP event was modelled, the frequency of the event in case it is included, and the representativeness degree for each analysis.

Table 6.1: Cases executed and analysed.

Case N°	Case name	Occurrence of HILP event	HILP event frequency	HILP event representativeness
1	BASE	✗	--	Zero
2	HILP_FULL_1Y	✓	1 year	Total
3	HILP_FULL_5Y	✓	5 years	Total
4	HILP_PART_1Y	✓	1 year	Partial
5	HILP_PART_5Y	✓	5 years	Partial

In addition, for each stochastic planning case listed in Table 6.1, the associated 18 deterministic portfolios are also generated, as explained in Section 4, for comparison purposes.

6.3.7 Stochastic expansion results – Resilience aware planning (methodology 2)

This section presents the results obtained from the different cases listed previously when the stochastic transmission expansion planning is made.

- **Investment portfolios on final epoch (2037)**

Figure 6.11 to Figure 6.14 show the investment portfolios obtained for the different ISP2022 original scenarios when the resilience-aware methodology is included in the stochastic transmission expansion planning.

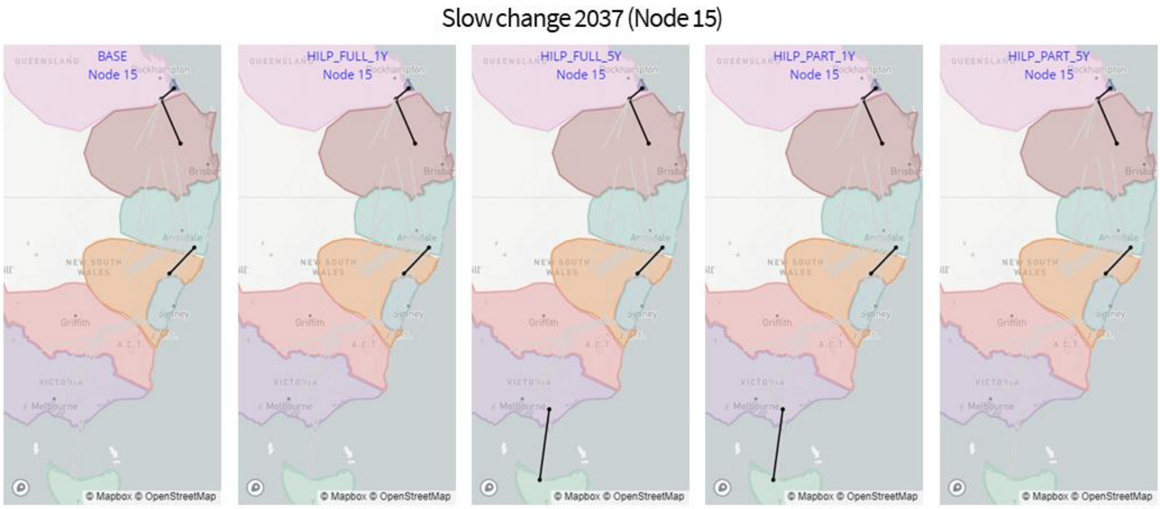

Figure 6.11: Investment portfolios obtained for Slow change in different resilience cases.

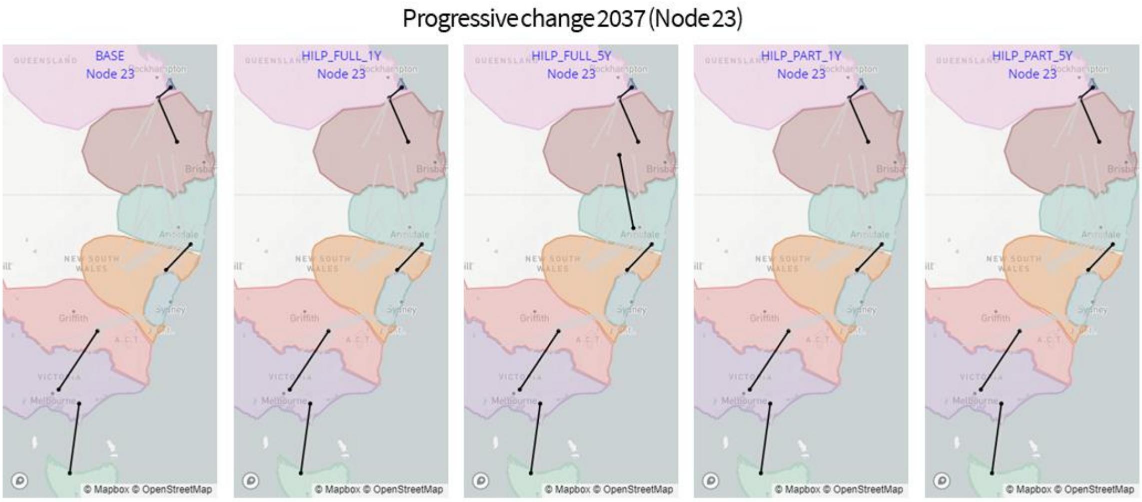

Figure 6.12: Investment portfolios obtained for Progressive change in different resilience cases.

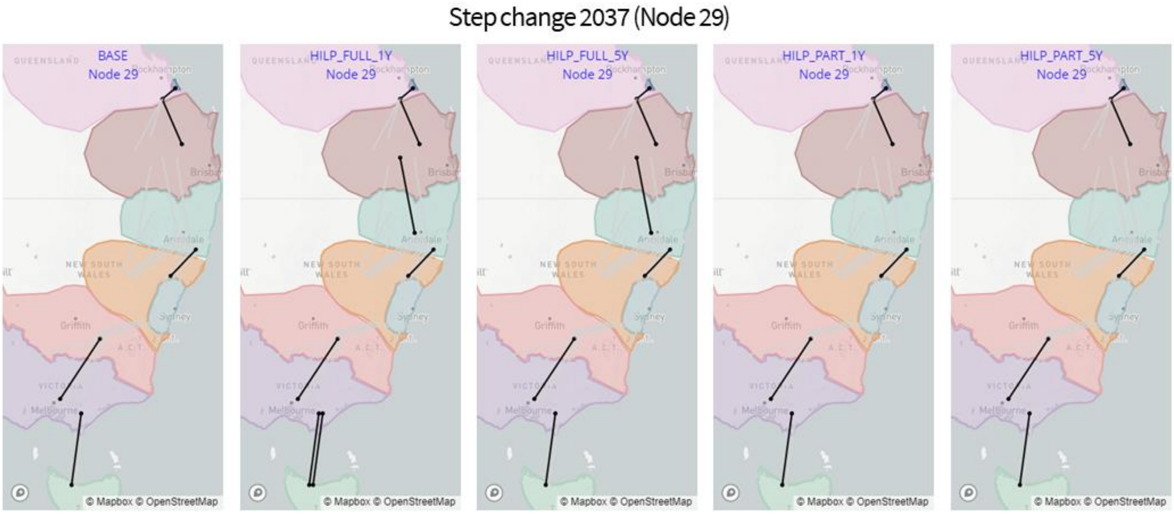

Figure 6.13:Investment portfolios obtained for Step change in different resilience cases.

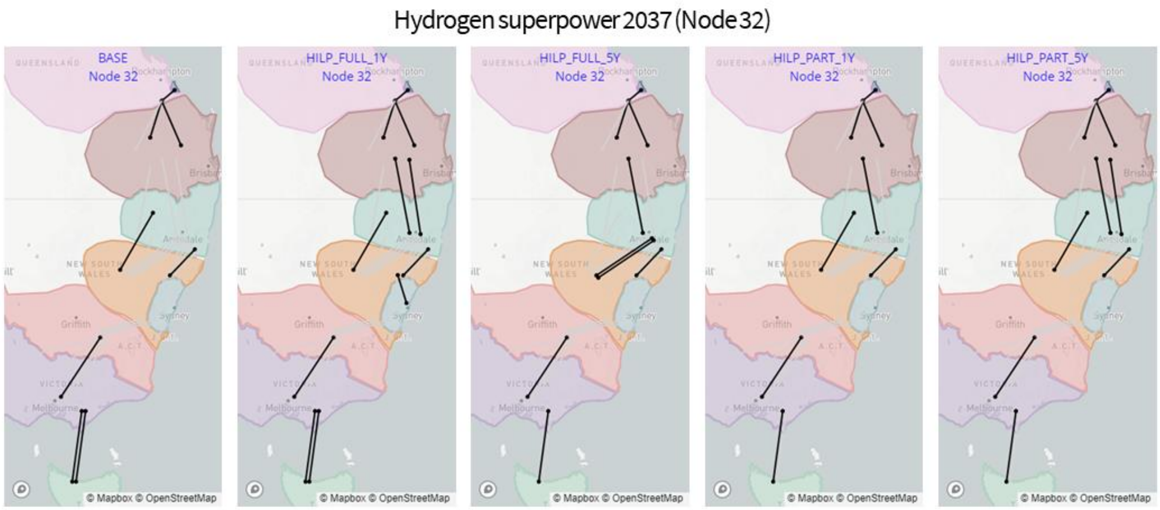

Figure 6.14:Investment portfolios obtained for Hydrogen Superpower in different resilience cases.

From the results, it emerges that when resilience assessment is included into the stochastic transmission expansion planning framework, different results are obtained in the final epoch (2037) compared to the base case. For example, in the Step change scenario (Node 29 - Figure 6.13), an additional link, specifically the TAS-VIC Option2, is built by 2037 when the case is set with 1-year frequency and full representativeness. For the same node, when the event is fully represented in the scenario tree, more investment is made and independently of the frequency of the event; in particular, the link NNSW-SQ Option 1 is built. Also, in the Progressive change scenario, when the event frequency is set to 5-year, the NNSW-SQ Option 1 is built, but this does not happen for the 1-year frequency. When the Hydrogen superpower scenario (Node 32 - Figure 6.14) is analysed, it can be seen that this is the scenario that drives more investment, even in the base case, where a double link between TAS and VIC, namely, TAS-VIC Options 1 and 2, is built, which can be explained by the higher demand values expected in that scenario.

It is also important to note that when the frequency and representativeness of the event differs, the final investment portfolios are also different. When the event is partially represented in the scenario tree, in general less investment is made compared to the cases when the event has full representativeness. For example, the links CNSW-NNSW Options 4 and 5 are not built in the partial representativeness case. Also, if the full and partial representativeness cases for the 1-year frequency (FULL_1YR and PART_1YR) are compared in the Hydrogen superpower scenario, three additional lines, NNSW-SQ Option 1, CNSW-SNW Option 1 and TAS-VIC Option 1, are built when there is a full representation, emphasising that a higher representation of frequent extreme events across the scenario tree drives more investment decisions to reinforce the system.

Delving into the specific results for the full representativeness case, it can be observed that the NNSW-SQ Option 1 is a common element in the portfolios obtained in Progressive Change, Step Change, and Hydrogen Superpower scenarios. This new link provides an additional transmission capacity of 1080 MW between the areas of QLD and NSW, which shows the higher demand and lower availability of renewable resources in the southern zone of the NEM, caused by the HILP event, leads to reinforce the northern area of the system.

Similarly, the TAS-VIC Option 2 link is also identified as an investment option needed to support the network in the 1-year frequency cases for the Hydrogen Superpower and Step Change scenarios. Its construction is contingent upon the development of additional links in the Queensland and New South Wales regions, which again underscores the importance of having a robust network capable of transporting resources from these areas to the affected regions during extreme events like the one modelled, providing enough transmission capacity to satisfy the demand.

Another noteworthy point is the phenomenon illustrated in Figure 6.14. Although the TAS-VIC Option 2 link is included in the portfolio in the base case, a shift in investment decisions is observed when the event occurs less frequently or has lower representativeness (FULL_5Y, PART_1Y, and PART_5Y cases). In these cases, the decision is made to invest in links in the QLD and NSW areas instead.

The results demonstrate that even when events are partially represented or less frequent, the resilience-oriented approach prioritises reinforcing the northern zone of the system. Although this may seem counter intuitive as the event occurs in the south, it can be explained by the availability of renewable resources in the northern region of the NEM, which can be used to meet the energy requirements during a HILP event in the southern regions.

- **Anticipative investment options**

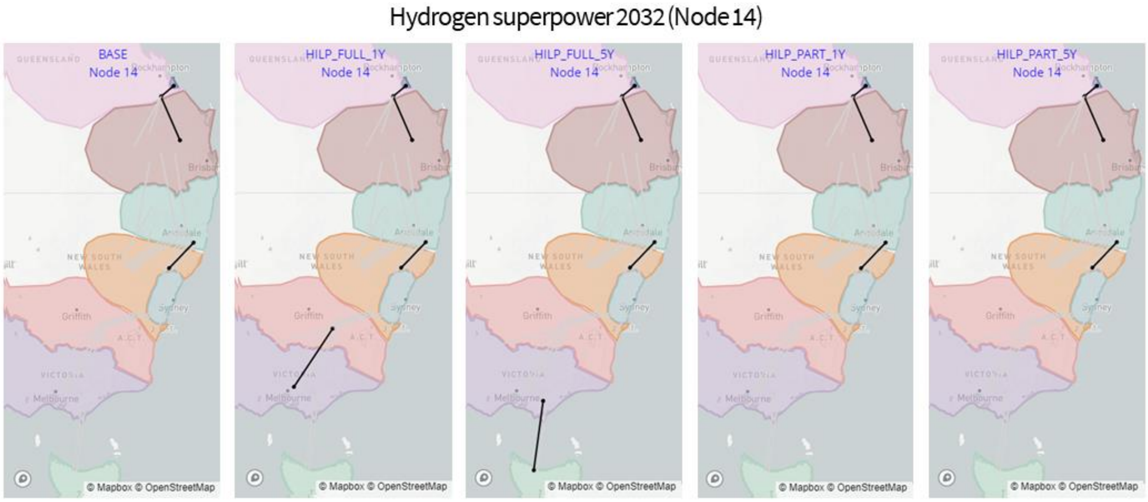

Figure 6.15: Investment portfolios obtained for Hydrogen Superpower in 2032 for different resilience cases.

In addition to a higher number of investments, it is also possible to note that when an extreme event is represented in the stochastic transmission planning process, some investment options are brought forward in time compared to the original decision in the base case. This indicates the need of the system to be reinforced early to avoid the effects that an extreme event could have on it. This anticipated decision of investing in transmission can be explained because the illustrative HILP event affects the system from early stages, thus the high peak and lower generation that occurs when the event takes place, causes investments to be brought forward. It can be inferred that constructing an additional link early on is more cost-effective than having higher amounts of unserved energy, which is highly penalised in the objective function.

Deepening into the investment decisions shown in Figure 6.15, for the FULL_1Y case, the anticipated link is the VIC-SNSW Option 6A, with a capacity of 1930 MW, while in the FULL_5Y case, the early investment is made in the VIC-TAS Option 1 with a capacity of 750 MW. These decisions show the need for early reinforcement of the southern zone of the system in response to the extreme event under consideration. Additionally, this highlights how the frequency parameter affects the model decisions and how the stochastic framework is capable to capture it. As the event is more frequent, the model invests in more transmission capacity than when the event has lower frequency. This can be also explained from an *insurance* perspective; as the model recognises that an extreme event is more frequent, it is more likely to invest in additional capacity, paying a premium for an asset that will protect the system from the worst performing conditions associated with the HILP event in the future.

6.3.8 Deterministic expansion results – Resilience aware planning

Additionally to the stochastic transmission expansion planning results, the deterministic studies for each possible scenario were also performed for comparison purposes. The portfolios obtained in the final epoch (2037) are shown in Figure 6.16 to Figure 6.19.

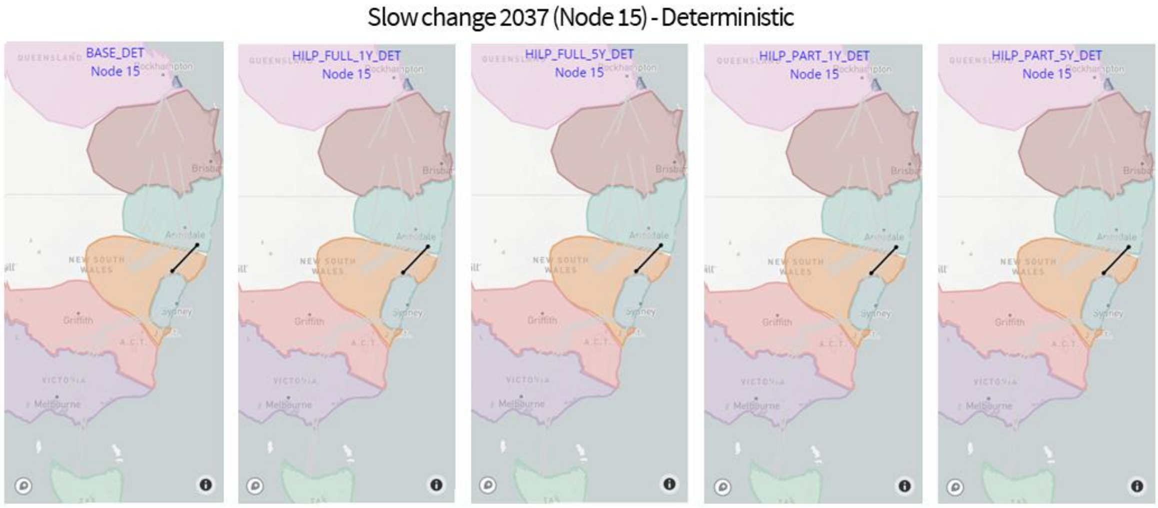

Figure 6.16: Deterministic investment portfolios for Slow change in 2037 for different resilience cases.

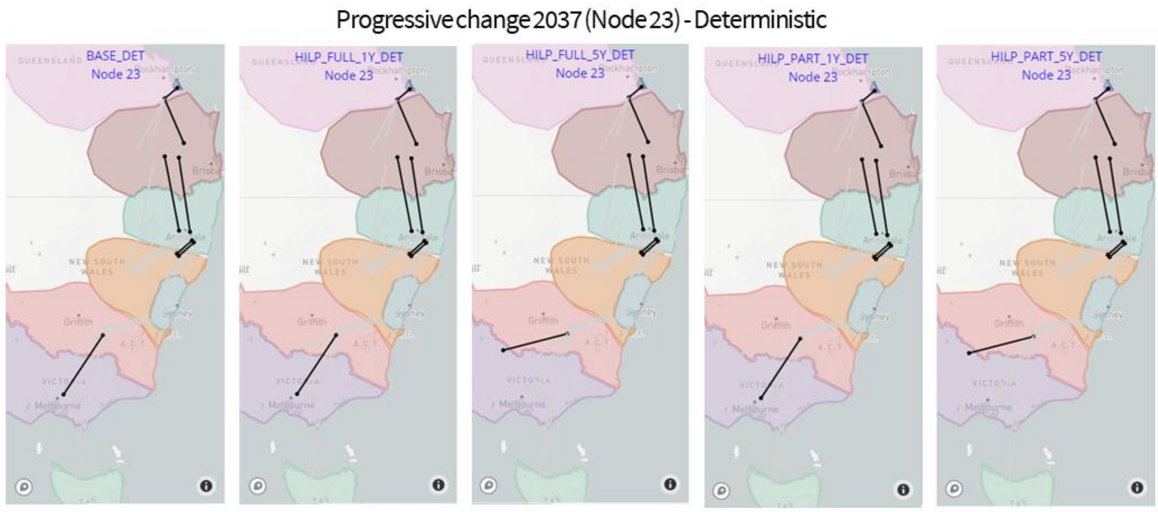

Figure 6.17:Deterministic investment portfolios for Progressive change in 2037 for different resilience cases.

Step change 2037 (Node 29) - Deterministic

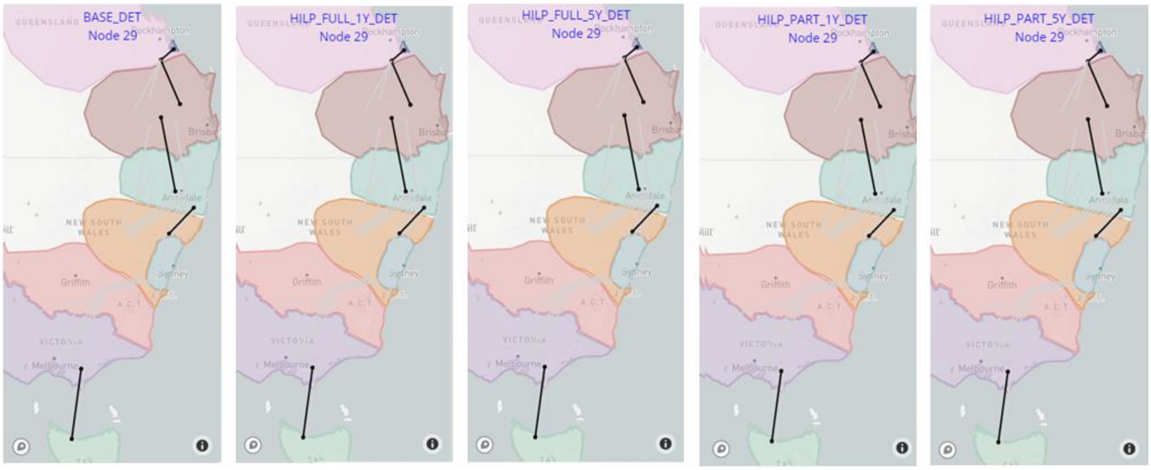

Figure 6.18: Deterministic investment portfolios for Step change in 2037 for different resilience cases.

Hydrogen superpower 2037 (Node 32) - Deterministic

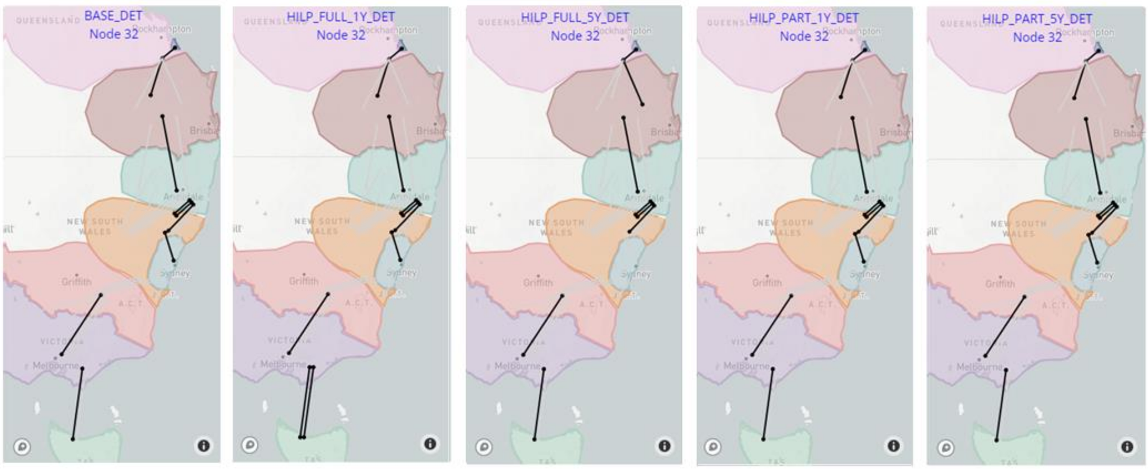

Figure 6.19:Deterministic investment portfolios for Hydrogen superpower in 2037 for different resilience cases.

The figures above illustrate the different transmission investment portfolios for the four ISP2022 scenarios when running a deterministic analysis and applying the methodology 2 to model extreme events within the planning framework.

For example, in the Slow change case (Figure 6.16), the only investment made throughout the five configurations of the study is the CNSW-NNSW Option 7 link, which occurs even when the extreme event is modelled using different frequencies and representativeness. The same happens for the Step change scenario (Figure 6.18), where there is no variation in the investment decisions across the five study conditions under consideration. In the cases of Progressive change and Hydrogen superpower, it is possible to observe slightly different portfolios, but still maintaining a similar structure. The similarity of results across the five conditions under consideration can be explained by the impossibility of a deterministic model to leverage value for a given reinforcement across scenarios. As discussed in Section 4.3, the deterministic scenarios are independent representations of the future, and the inclusion of a highly unlikely and short event such as the one modelled may not change the investment decisions. The only differences that are seen are the additional investment in the TAS-VIC Option 2 in the node 32 (Figure 6.19) for the FULL_1Y case and the switch between VIC-SNSW Option 2 VNI West and VIC-SNSW Option 6A in the node 23 (Figure 6.17). The first difference can be explained as a necessary investment for the case to properly address the requirements for the demand, and the second one is not related to capacity itself, as both mentioned options have a capacity of 1930 MW, showing that additional capacity needs for the system were not addressed in the decision.

6.3.9 Cost results – Resilience aware planning

In order to assess the economic side of the proposed resilience methodology, a brief cost analysis is conducted through the costs of each study case. In the Figure 6.20, the expected costs are presented for each analysed case.

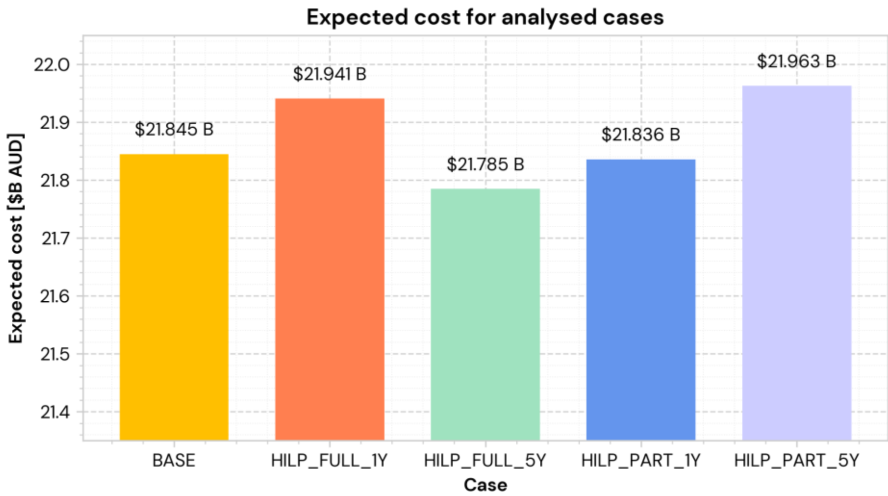

Figure 6.20: Expected costs for the analysed resilience cases.

It can be observed that the expected costs for each of the cases are around $21.8 and $21.9 billion. In other words, despite the existence of different transmission investment decisions and more or less extreme operating conditions given by the occurrence of an extreme event during the operation of the system with a certain frequency, the expected costs remain relatively stable compared to the base case (-0.02% to 0.05% difference). This suggests that, to some extent, the possibility of making additional investments in the face of extreme events allows the system to protect itself correctly, avoiding a considerable increase in total costs and allowing a secure and resilient operation for a broader set of possible conditions.

6.3.10 Two-step resilience aware stochastic planning (methodology 3)

This section introduces and reviews the implementation of methodology 3 (Two-step resilience aware stochastic planning) using the cases shown in Table 6.1 and event structure described in sections 6.3.5 and 6.3.6. This methodology involves a two-step process: first, planning for reliability, and second, developing new plans accounting for resilience using the remaining transmission options. The results are compared to those obtained through methodology 2.

- **Investment portfolios in final epoch (2037)**

Figures Figure 6.21 to Figure 6.25 show the resulting investment portfolios obtained by applying the two-step resilience aware methodology proposed to incorporate resilience consideration in the stochastic power system expansion planning. The “RELIABILITY” label indicates the investments required to comply with the adequacy and security standards of the system, while the “RESILIENCE” label corresponds to the portfolios resulting from applying the second stage of the methodology for the different parameter configurations introduced previously in Table 6.1.

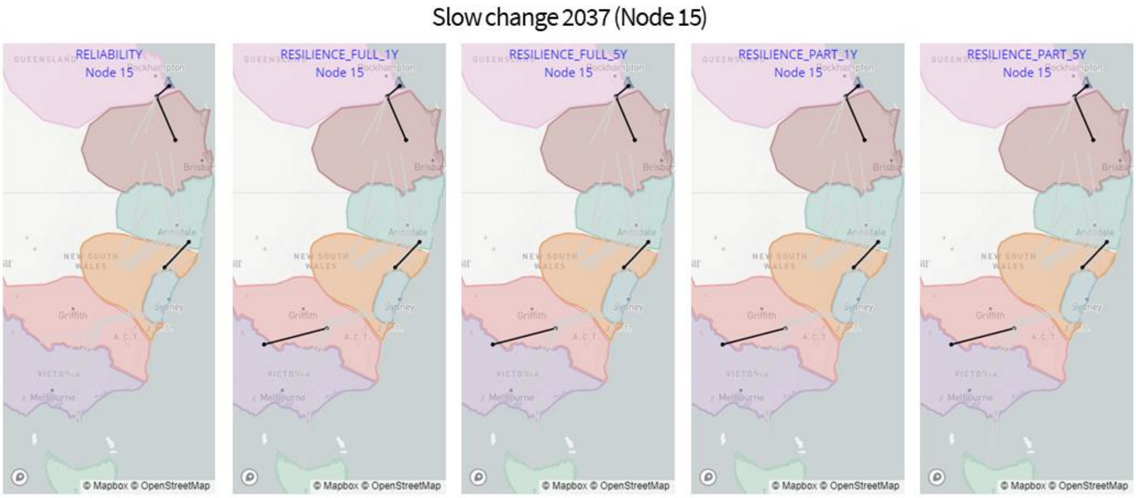

Figure 6.21: Investment portfolios obtained for Slow change in 2037 with methodology 3.

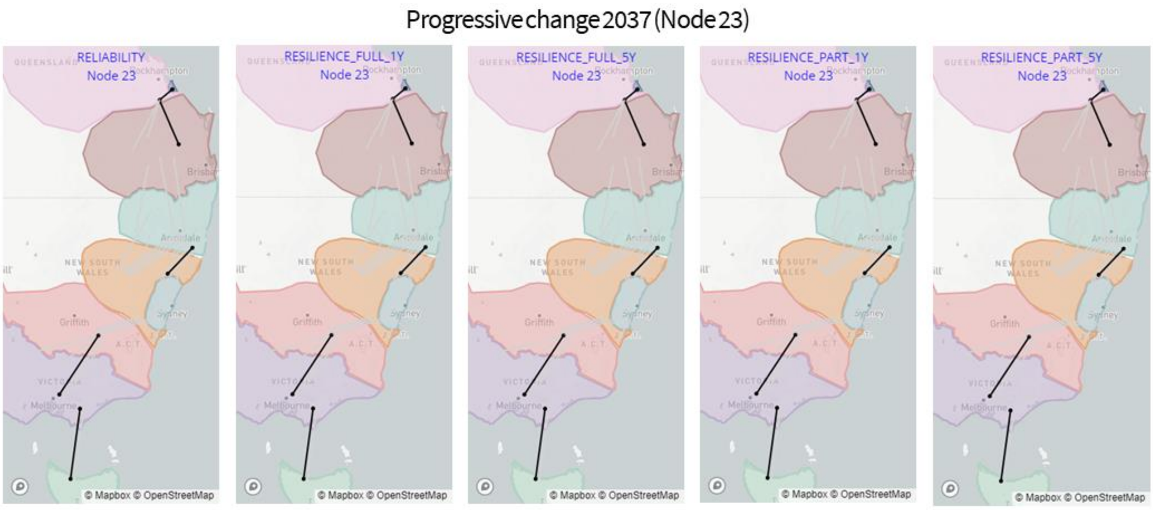

Figure 6.22: Investment portfolios obtained for Progressive change in 2037 with methodology 3.

Step change 2037 (Node 29)

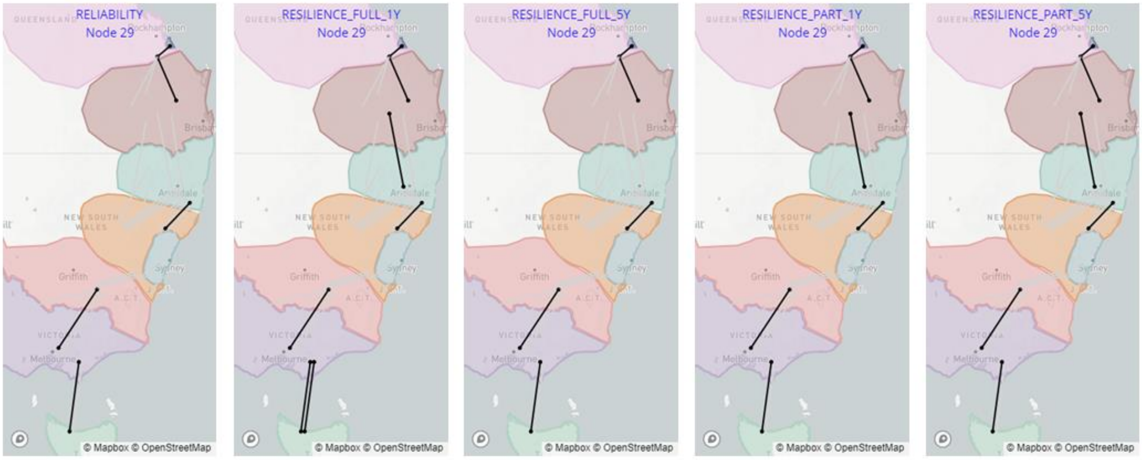

Figure 6.23: Investment portfolios obtained for Step change in 2037 with methodology 3.

Hydrogen superpower 2037 (Node 32)

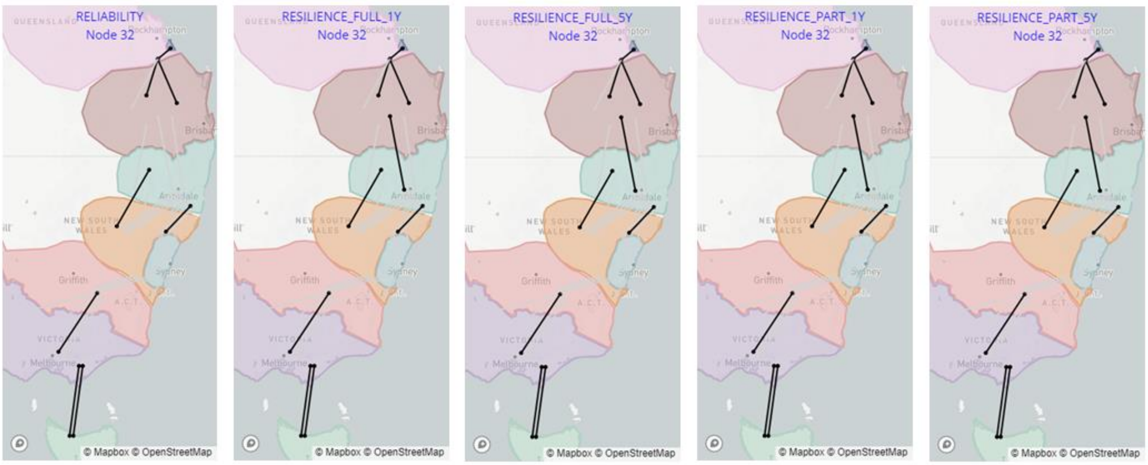

Figure 6.24: Investment portfolios obtained for Hydrogen superpower in 2037 with methodology 3.

The proposed methodology allows for sequential investment decisions to be made, which reveal additional investment opportunities in two steps: first, planning for reliability and making the necessary investments to ensure security and adequacy, and second, planning for resilience. This approach uncovers complementary investments when considering both reliability and resilience in two stages.

For instance, consider the results for Slow change on node 15 (Figure 6.21). When the system is expanded just considering reliability, the link VIC-SNSW Option 2 VNI West is not taken as part of the plan, while that option appears in every resilience portfolio, suggesting its significance in preparing the system to deal with the extreme event. If the step change scenario (Figure 6.23) is analysed, the NNSW-SQ Option 1 appears as an investment decision selected across the four resilience cases under consideration, while the TAS-VIC Option 2 is only necessary when the event has a 1-year frequency and full representativeness (FULL_1Y case), indicating the need to have more reinforcements in the network when the event becomes more frequent and it is fully represented in the scenario tree.

If the Hydrogen Superpower scenario results are reviewed, the same trend is observed. While the reliability portfolio sets an initial set of investments to comply with the related constraints and requirements, when the second step for resilience is applied, additional network reinforcement is required. Specifically for that scenario, the NNSW-SQ Option 1 becomes part of the final set of investments.

The portfolios resulting from the use of methodology 3 reveal the need for additional resilience investments beyond the reliability portfolio. This is seen in the case of NNSW-SQ Option 1, which becomes a necessary investment to cope with extreme event conditions. When comparing methodologies 2 and 3, the latter fixes the reliability portfolios before deciding on resilience options, resulting in a more uniform expansion of investments across cases. However, key investments like TAS-VIC Option 2 and NNSW-SQ Option 1 are necessary in both approaches, indicating the need to utilise resources available in the northern areas of the NEM and requiring additional capacity between Victoria and Tasmania for the analysed illustrative HILP event.

- **Anticipative investment options**

Anticipative investment decisions are also observed when applying this methodology. Specifically, for the node 14 (Figure 6.25), the VIC-SNSW Option 6A is advanced one epoch when the event has full representativeness and its frequency is set to 1 year. It is important to emphasise that this link is also part of the reliability portfolio in node 32, which means the resilience requirements directly affects the timing of the reliability-related investment decisions.

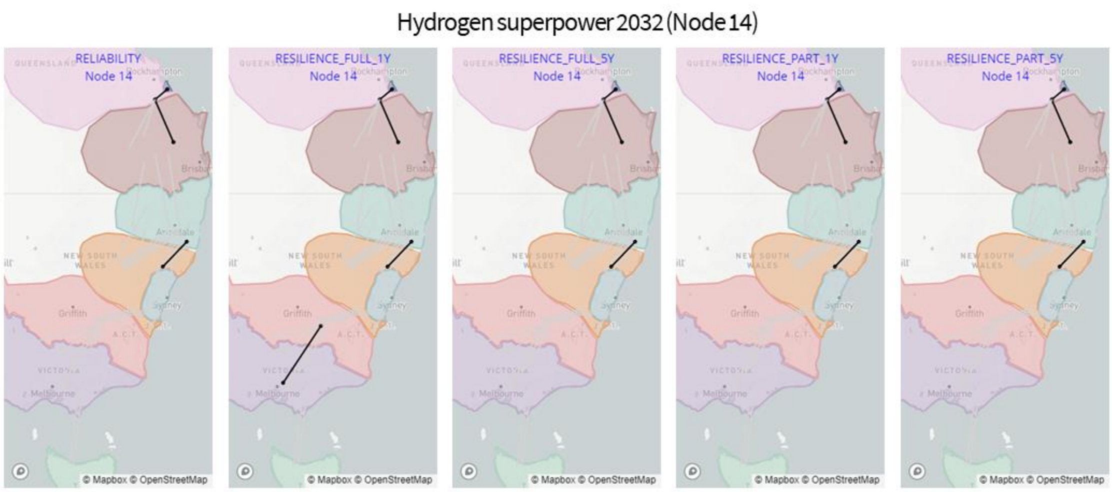

Figure 6.25: Investment portfolios obtained for Hydrogen superpower in 2032 with methodology 3.

Additionally, by looking the FULL_5Y case for both methodologies 2 and 3 in Figure 6.15 and Figure 6.25, respectively, it is seen that in methodology 2, the TAS-VIC Option 2 was advanced, while in methodology 3 that does not occurs. These differences can be mainly attributed to the fact that in methodology 2, the assessment for reliability and resilience is done concurrently, whereas in methodology 3, the reliability investments are already in place when resilience is assessed, limiting the scope of the optimisation problem for finding new cost-effective investments that can enhance resilience capacity while also minimising costs.

6.4 Joint work with EPRI: Resilience expansion planning

This section presents a summary of the model and case study applications developed by EPRI in the context of this project. EPRI's contribution is particularly insightful in that it is linked to a number of industry-led developments that are currently occurring with several utilities, especially in a US context, and it provides additional and further views on potential methodological developments for resilience studies. For the full report see Appendix D.

6.4.1.1 Problem Statement and Context

Power system resilience is essential as grid planners confront natural disasters such as floods, fires, droughts, storms, extreme heat and cold, as well as human-driven cyber and physical attacks. These hazards bring new design challenges to planners because the capacity planning tools that exist today were designed for dispatchable resources in a stable climate. As planners face more frequent and severe hazards, new tools are needed to bring risk into planning decisions and build resilient power systems.

Industry planners have undertaken significant efforts towards resilience planning. Many utilities have conducted extensive vulnerability assessments for the relevant regional hazards, the vulnerabilities of individual assets, the consequences of impacts, and the options for mitigating these risks. Regional transmission organisations have also, in many cases, conducted detailed studies examining resilience challenges, often in response to a significant disruption or to prepare for anticipated electrification and high levels of renewable integration.

But for the most part resilience studies are separate undertakings from the main expansion plan; most resilience considerations are not built into capacity planning models but instead explored through distinct studies. Some academic and industry research organisations have begun to consider resilience challenges, such as modelling common-mode outages or methods for selecting important events, but this work is still nascent and has not yet been adapted to industry practice in a significant way.

However, separating resilience studies from the primary planning process misses a major opportunity to build resilience into the initial plan. Many of the most economical resilience improvements are likely to come from changing the sizing, timing, and location of investments, as well as selective hardening investments. And this sort of system-level resilience is best identified by bringing extreme events into the model where candidate plans are first developed.

6.4.1.2 Proposed solution

EPRI's approach is thus also to represent extreme events and disruptive hazards directly in capacity planning models, in line with the methodologies presented above. They develop a formulation that includes hazard-driven load changes, deratings and shutdowns of generation and transmission assets, the risk of damage costs to grid components or outside parties, hardening options to mitigate those disruptions and damages, and the costs and operational implications of those hardening investments.

Rather than include disruption and damage costs in the planning objective, EPRI proposes constraints that limit the risk of damages and disruptions across the event set according to risk tolerance levels chosen by planners. This avoids the need to assign probabilities to intrinsically unlikely events and then balance these probabilities with those of normal operating conditions. This approach is different from the methodologies presented before as methodology 2 and 3 were focused on using the structure of stochastic planning to define new events and assign probabilities of occurrence using transition probabilities between nodes and/or using weights to determine the relevance of the typical weeks of operation. The risk tolerance settings also allow planners to explore gradually more robust plans, tightening from a baseline to a fully robust plan. This flexibility allows planners to conduct a sensitivity analysis on the impacts of risk tolerances.

Several supporting methods are presented, which are helpful to reduce computational requirements and give planners more flexibility when deploying the above approach. These supporting methods include ways to select important events and ways to tailor the model's risk limits to the aims of the study.

6.4.1.3 Value

The findings of EPRI's work can be divided into two categories: methodologically relevant findings, and potential insights planners might find by implementing the various approaches.

First, methodologically, many resilience considerations can be built into existing planning models with familiar modelling techniques and without excessive computational burden. Good examples of this are the three methodologies we introduced in the previous sections of the discussion about resilience. Also, hazard-driven asset deratings and shutdowns, damage costs, various hardening options, performance changes from these hardening options, and sophisticated risk profile limits can all be built into capacity planning formulations with computationally efficient optimisation practices. Modelers have many options that can be selectively chosen to improve resilience representations in planning tools.

There are still barriers to deploying these features, however. Collecting the necessary data and generating credible hazard events is a substantial task. And then selecting a small number of important events is challenging. EPRI describes that, while satisfactory event selections can be found using only the attributes of the events (such as the total capacity at risk), finding a robust event sample generally requires simulating the larger event set under several candidate expansion plans, which is computationally burdensome. Still, these obstacles are not insurmountable and should not prevent planners from including at least some resilience features in models.

Second, results from an illustrative test system suggest that planners can gain a number of insights from resilience planning with the proposed approach. One of the main mechanisms for extracting these insights is through gradually tightening risk tolerances on successive optimisation runs, which lets planners compare a baseline plan to progressively more robust solutions. This approach aligns well with the parametric risk analysis conducted in the section about risk control in stochastic planning; however, instead of looking at the total cost of operation, the risk tolerance can be measure through a different metric (for instance expected energy not supplied). Planners can then investigate which system configurations and adaptation options are most cost-effective at a targeted risk level.

As we have already partially discussed in the studies about the tree methodologies that were proposed earlier, EPRI shows that substantial resilience improvements can be obtained at low cost by prudently upsizing some transmission investments, building transmission early, and changing the location of planned projects. At tighter risk limits, selective transmission hardening investments are a key part of a more robust plan, but this comes at a higher cost. Gradually tightening the risk limits will help planners determine which adaptation investments should be prioritised and the cases in which non-capacity options may be a better alternative.

Ultimately, EPRI's modelling tools will provide insights to planners about how resilience can be economically built into the initial grid plan rather than added as a costly afterthought.

6.4.1.4 Final Thoughts Next Steps

While this work is demonstrated through wildfire and heat hazards that are relevant to the Australian power system, the next steps are to demonstrate the work on large-scale systems that realistically represent an existing power grid. This includes making regional climate projections, refining hazard representations in events, and making detailed investigations into asset-specific vulnerabilities and performance characteristics.

Finally, the capacity planning solutions need to be integrated with other planning functions such as resource adequacy assessments, network stability analysis, and production cost and market simulations. The real measure of a capacity expansion model's success is an improved candidate plan as evaluated by the full suite of planning processes.

7 Effect of new technologies in the planning problem: Hydrogen-related assets.

Most energy system planners in countries with an abundance of renewable energy resources, including AEMO in Australia, now consider in their planning scenarios the potential deployment of large-scale green hydrogen production (through electrolysis) for export of green fuels and decarbonisation of heavy industry, which will lead to a massive increase in demand associated with such developments and thereby create major interactions between electricity and future green hydrogen systems. In addition, as the advent of large-scale green hydrogen production raises the question of whether to transport[12] VRE as molecules in hydrogen pipelines or as electricity in electricity transmission lines, the aim of this section is to evaluate the value and impact of considering hydrogen pipelines as potential options to transport VRE from REZ *directly* to hydrogen export ports. Towards this aim, the planning model is extended to a *greenfield* multistage integrated electricity and hydrogen transmission infrastructure planning model that incorporates hydrogen pipelines as transport options along with or *in lieu* of electricity lines. This greenfield integrated model is then demonstrated on an initial case study that considers all the REZ stipulated in AEMO's ISP 2022 [1] and connects them with provisional corridors to the hydrogen export ports whose demands are specified in AEMO's ISP 2022 under the hydrogen superpower scenario [1]. The case study is conducted with VRE traces and hydrogen export demand for years (epochs) 2027, 2032, and 2037.

Three different technologies, namely, hydrogen pipeline links (including carbon steel pipelines and compression stations), HVAC transmission links (including overhead lines (OHL), transformer substations, and reactive power compensation), and HVDC links (including OHL and converter stations) are considered as options in the provisional connection corridors. These proposed provisional corridors are shown in Figure 7.1 and the total yearly hydrogen export demand is shown in **Error! Reference source not found.**.

Table 7.1. Hydrogen export demand across the three considered epochs

	Epoch		
Unit	**2027**	**2032**	**2037**
Mt/year	0.20	1.08	3.53
m^3/s	75	400	1,310
MW	907	4,847	15,850

* An HHV of 141.876 MJ/kg and a density of 0.0853 kg/m^3 are used for hydrogen.

[12] The terms "transport" and "transmission" are used interchangeably in this section.

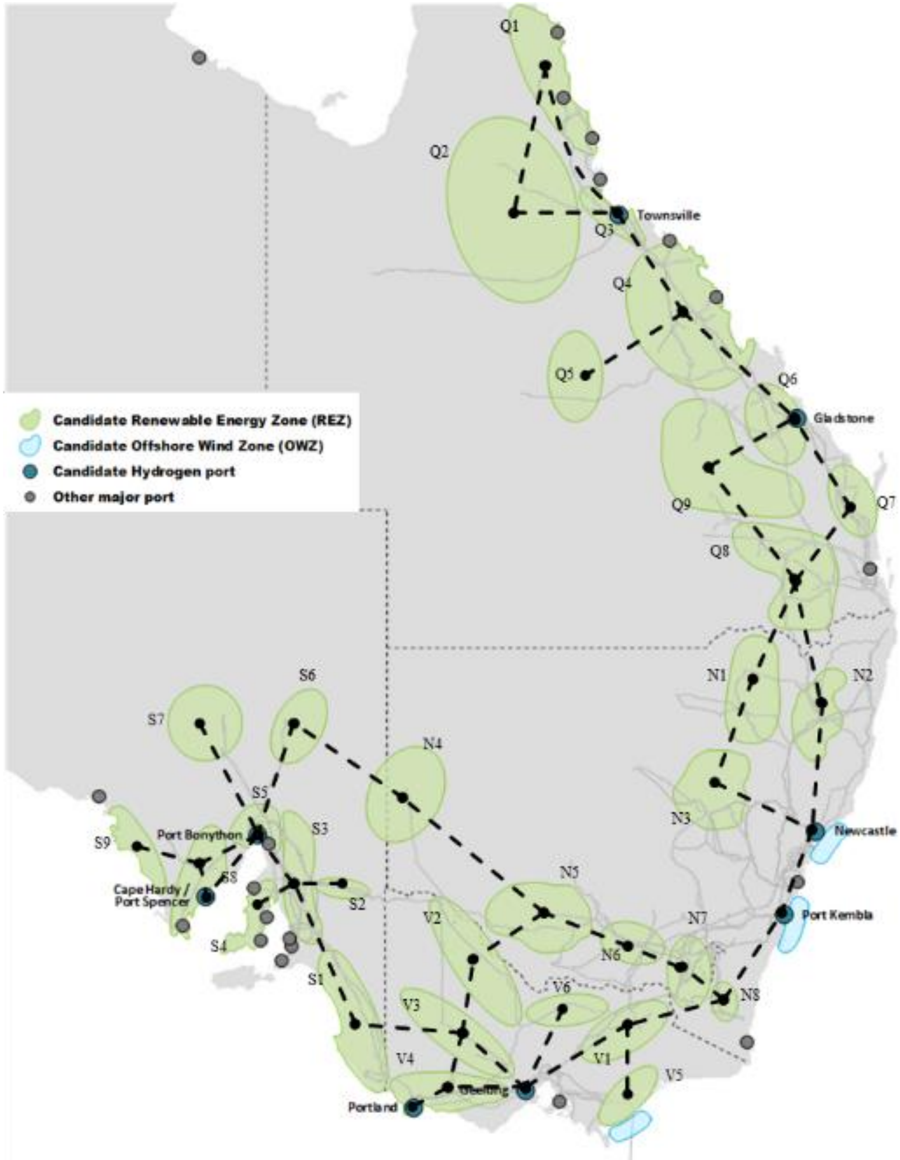

Figure 7.1. Dashed lines delineating the proposed provisional transmission corridors connecting REZ and H_2 export ports. The underlying map is obtained from AEMO's ISP 2022 [1]

The analysis is this section uses the same HVAC and HVDC options described in the REZ augmentation options and the flow path augmentation options in AEMO's ISP 2022 [1]. These costs and technical assumptions of HVAC and HVDC links are shown in Table and Table in Appendix C, respectively. Hydrogen pipeline (and compression) capital and operating costs, as well as technical details, are obtained from publicly available reports from the peak body representing Australian pipeline infrastructure [134]. These costs and technical assumptions for hydrogen pipeline links are shown in Table in Appendix C.

Under the cost and technical assumptions in this section, the optimal greenfield multistage integrated model chooses hydrogen pipelines exclusively as the optimal transmission infrastructure for the case study in Figure 7.1 and **Error! Reference source not found.**. The results are detailed in Table 7.2 which shows where the hydrogen pipelines are installed along with their diameter D_n, steady-state throughput, and NPV over each epoch (year 2022 is chosen as the reference year for the NPV computations). The total infrastructure NPV for this optimal solution is $3.09 billion. This optimal solution is also shown in Figure 7.*2* on the Australian east coast map for epoch 2037. It should be noted that the capacity of a pipeline of diameter D_n decreases with distance. Please refer to [135] for more details on the relationship between gas pressure, gas flow, and distance. Moreover, as can be seen from Figure 7.*2* and Table 7.2, the steady-state throughput of the hydrogen pipelines installed in 2027 and 2032 are not the same as the ones in 2037.

Table 7.2. Results of the optimal integrated transmission infrastructure case study over the three considered epochs.

Corridor		Distance (km)	D_n (inch)	Steady-state throughput (MW)	NPV (MAUD)
From	To				
			2027		
V4	Portland	123	14	907.27	316.74
			2032		
Q6	Gladstone	118	16	1518.67	334.01
N8	Port Kembla	265	16	1639.77	439.15
			2037		
Q2	Townsville	292	18	2174.28	477.73
Q3	Townsville	49	8	781.31	99.29
Q7	Gladstone	310	18	2183.35	496.10
N2	Newcastle	280	20	2962.61	557.30
N8	Port Kembla	260	12	974.27	251.15
S5	Port Bonython	85	8	616.99	117.64

Under the cost and technical assumptions (see Appendix C) of the specific case study in this section, in which a *greenfield* integrated electricity and hydrogen infrastructure planning model is used to find the most cost-effective infrastructure design that connects the REZ in AEMO's ISP 2022 (see Figure 7.1) *directly* to a single type of demand, namely large-scale green hydrogen (i.e., molecules), results show that hydrogen pipelines are more cost-effective than their electricity counterparts under the specific corridor lengths in this case study (see Figure 7.1). This is another way of saying that in this case it is more cost-effective to co-locate large-scale electrolysis and VRE, and transport the produced green hydrogen in pipelines, as opposed to locating large-scale electrolysis at the location of the hydrogen demand (in this case the export ports). In fact, if hydrogen pipelines are removed from the considered set of options, the greenfield integrated model then chooses HVAC links exclusively as the most cost-effective technology (compared to HVDC links), for a total transmission infrastructure NPV of $4.4 billion – a 42% increase over the integrated electricity and hydrogen transmission case. Furthermore, if HVDC links are the only considered option, the total NPV of the optimal infrastructure design would further increase to $12.67 billion, a 310% increase compared to the integrated electricity and hydrogen transmission case. It should be noted that the longest corridor in Figure 7.1 has a distance of 480km (N4 to N5), which explains why HVAC options are preferred over their HVDC counterparts (in the case without hydrogen pipeline options). These results are congruent with HVAC vs HVDC comparisons in existing literature, which identify a break-even distance of around 600km, beyond which HVDC becomes more cost competitive [136].

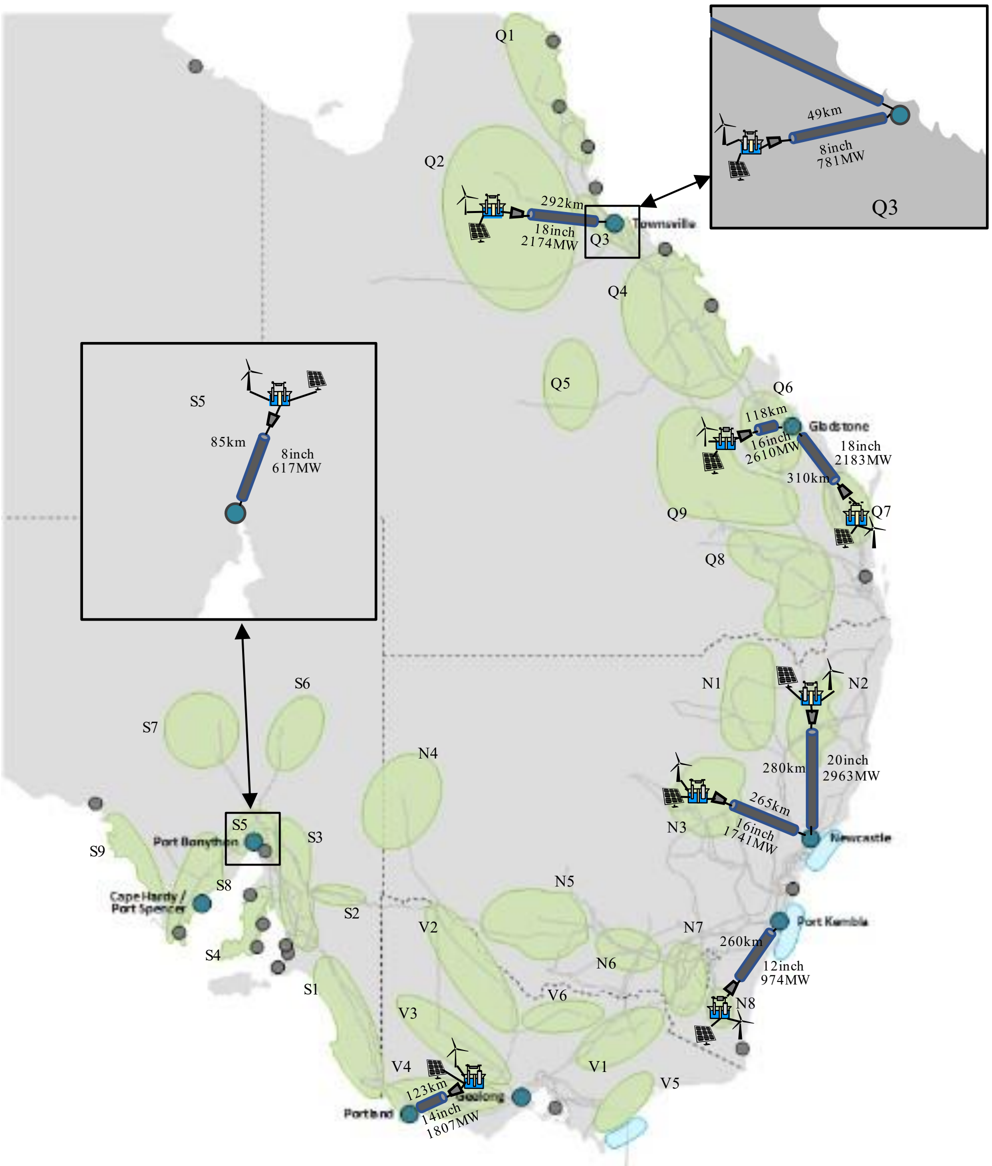

Figure 7.2. Optimal integrated infrastructure solution at epoch 2037

Being preliminary, these findings should not be viewed as recommendations for AEMO to co-optimise electricity and hydrogen infrastructure networks, but rather as initial steps in quantifying the potential merits of considering hydrogen pipeline options alongside electricity options to achieve an overall cost-efficient whole-system planning.

8 Conclusions

This report has provided an in-depth analysis of multi-stage stochastic planning for power system expansion under uncertain conditions, using an instance of the Australian power system to illustrate the effects of the models being proposed. The report has been structured to present the methodology, analysis, and results in a clear and concise manner, enabling readers to follow the research process and understand the key findings.

The results of the study demonstrate that stochastic planning has the capacity to identify flexible investment options (that is, assets capable to provide value across scenarios), enabling planners to control the risk of the portfolio. The approach is capable of readily extending the reliability-oriented model to identify investment options capable of enhancing resilience. Furthermore, the analysis shows that stochastic planning can be extended not only to make decisions about new transmission and storage assets, but also hydrogen-related infrastructure.

Overall, the findings highlight the value of using multi-stage stochastic planning in power system expansion decision-making. The approach provides a comprehensive framework for addressing the complexities associated with strategically expanding power systems under uncertain conditions. These findings have significant implications for the power industry, as they offer a practical and effective means of planning for future power system expansion and ensuring the reliability and resilience of the power grid.

It should be noted that the aim of the project was not to compare results with those obtained by the ISP, also because only a few representative time series profiles were used, but rather to illustrate the features and potential benefits of alternative approaches.

Future work in this domain includes analysing the role of distributed energy resources and hydrogen assets in the context of resilience-oriented stochastic planning.

Flexible expansion plan based on multi-stage stochastic planning

This study has demonstrated the effectiveness of multi-stage stochastic planning in addressing the complexities associated with power system expansion under uncertain conditions. The use of a scenario tree to capture uncertainty in various parameters such as load, renewable energy capacity, unit decommission, investment, and operation costs has allowed for the identification of optimal investment portfolios that minimise total expected costs while satisfying various investment and power system constraints. The results of this study show that flexible investment options can form the backbone of the future network's reinforcement and that interconnection capacity between regions plays a crucial role in minimising total expected costs.

Furthermore, this study highlights the importance of considering the representation of operation in investment decisions. The reduction of operational representation may lead to substantially smaller total investment and operation costs, but this may result in a poorly performing optimal portfolio when tested against a more robust representation of operational conditions. Overall, this study provides valuable insights into optimal investment decision-making in power system expansion under uncertain conditions and can inform policy decisions in the transition to a more sustainable and reliable energy system.

Deterministic planning

This section of study compared different approaches for making investment decisions in transmission systems and shows that using different metrics and procedures to determine the optimal investment portfolio can result in significantly different investment strategies, particularly in conditions of deep uncertainty. The stochastic planning approach is more effective than deterministic-based methodologies such as LWR/LWWR in addressing planning uncertainty. This is evidenced by the case studies conducted for the Australian power system, where the deterministic approach incurs higher expected total costs and considerably elevated costs for the worst-performing scenarios.

The difference in outcomes is due to the distinct objectives of each metric. Stochastic planning aims to minimise expected costs, resulting in an investment strategy with the lowest possible expected costs, which is lower than those achieved by LWR/LWWR approaches that prioritise minimising the worst regret. However, minimising the worst regret through deterministic analysis leads to riskier portfolios when looking at higher worst-case cost, compared to stochastic expected cost minimisation. Regrets represent a relative measure of scenario performance and do not ensure the containment of impacts of extreme scenarios, as stochastic planning implicitly does, but merely reduce the worst difference between scenario costs.

In general, the outcomes reveal how employing a stochastic planning methodology can present a more integrated viewpoint across all potential scenarios, leading to the creation of development paths that are inherently less costly and risky when compared to an overall perspective based on decisions made across multiple independent deterministic scenarios.

Controlling the risk of the portfolio

The study highlights the importance and benefits of incorporating risk management principles when defining the optimal portfolio of investments for power systems. It demonstrates that controlling expected cost and risk are competing objectives in portfolio selection, and that introducing flexible technologies can reduce both expected costs and extreme outcomes simultaneously. The use of a risk-aware stochastic planning model, which includes a user-defined risk parameter, allows decision-makers to balance their position on risk. This model enables the definition of the optimal risk-aware portfolio for the system by determining an efficient frontier that represents the optimal balance of cost and risk. The study identifies that an intermediate risk aversion level offers the best trade-off between risk and cost, reducing risk by almost as much as the fully risk-averse case but with a smaller premium to be paid in terms of expected cost.

The analysis also highlights the importance of understanding risk metrics and identifies the most widespread and relevant metrics for risk analysis: Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR). The study demonstrates that CVaR is preferred over VaR as a risk measure for transmission expansion planning problems, particularly in cases where resilience against high-impact, low-probability events is essential. The study investigates the role of storage in risk-aware planning and identifies that co-optimising storage along with transmission lines can help reduce the risk of the portfolio by enhancing system performance in the most expensive scenarios. This also suggests that the proposed risk-aware stochastic planning approach can be suitably adopted to reveal cost-risk trade-offs and benefits that integrated investment in a wide range of technologies (beyond transmission-only assets) could bring.

Methodologies to incorporate resilience analysis in stochastic planning

Extreme events, specially weather-related ones, pose a significant threat to power system infrastructure and have caused substantial economic damage to power system globally. As a result, power system resilience has become a critical focus for researchers and policymakers to ensure the system's ability to withstand high-impact, low-probability events and adapt to future occurrences.

The report highlights three methodologies for studying the effect of extreme events in power system planning, with the results indicating that incorporating resilience aspects into the planning approach yields different investment portfolios in the final epoch, with more investment made when extreme events have a higher frequency. Anticipative investments also occur when an extreme event is represented, indicating the benefits of early system reinforcement using flexible investment options. Moreover, the stochastic approach allows for greater flexibility and variation in investment decisions while maintaining expected costs stable relative to the reliability-oriented planning approach.

Also, EPRI provided an in-depth exploration of models and approaches that could be utilised to integrate resilience into planning, with a particular emphasis on stochastic planning in industry-based projects in the United States. The analysis highlighted the significance of detailed modelling of extreme event characteristics that may impact the system and managing the computational complexity involved in such studies.

Overall, this study emphasises the need for continued research and development in power system resilience to strengthen the system's ability to withstand extreme events and ensure sustainable and reliable power supply for communities globally. By adopting and integrating resilient planning approaches and investing in infrastructure reinforcement, it is possible to create a more robust and adaptable system that is better prepared for future challenges.

Role of hydrogen infrastructure

This report presents a greenfield multistage integrated electricity and hydrogen transmission infrastructure planning model as a proof of concept to quantify the impact of large-scale green hydrogen production for export on investment planning. The model is applied to a case study that examines the cost-effectiveness of different transport infrastructure options to connect REZ and hydrogen export demand in Australia's hydrogen superpower scenario.

When large-scale green hydrogen export is considered as a separate demand that is assumed will be satisfied solely from the REZ in AEMO's ISP 2022, results of the developed greenfield multistage integrated electricity and hydrogen transmission infrastructure planning model suggest that hydrogen pipelines are more cost-effective than their electricity counterparts under the specific corridor lengths in this case study. The proof-of-concept case study proposes provisional corridors connecting renewable energy zones and hydrogen export ports in the superpower scenario of AEMO's ISP for years 2027, 2032, and 2037. Without hydrogen pipelines as options, the NPV of the chosen optimal infrastructure, which consists of only HVAC transmission links, increase by 42%. Finally, if only HVDC options are considered, the NVP increases by 310%. Since the longest corridor is this greenfield case study has a length of 480km, these results are congruent with HVAC vs HVDC comparisons in existing literature, which identify a break-even distance of around 600km, beyond which HVDC becomes more cost competitive.

It should be re-emphasised that the findings under this section are *preliminary* and are therefore not intended to provide recommendations for AEMO to co-optimise electricity and hydrogen infrastructure networks. More studies are needed to better understand the value of including hydrogen pipelines in the co-planning enterprise.

8 References

[1] AEMO, "2022 Integrated System Plan For the National Electricity Market," 2022. Accessed: Sep. 29, 2022. [Online]. Available: https://aemo.com.au/-/media/files/major-publications/isp/2022/2022-documents/2022-integrated-system-plan-isp.pdf?la=en

[2] L. Zhang, S. Püschel-Løvengreen, G. Liu, R. Laird, and P. Mancarella, "Power System Planning Australian Research Plan for CSIRO-Global Power System Transformation Consortium." Accessed: Aug. 03, 2022. [Online]. Available: https://www.csiro.au/-/media/EF/Files/GPST-Roadmap/Topic-4-Planning-Final-report_with-AltText-2.pdf

[3] P. Mancarella, L. Zhang, and S. Püschel-Løvengreen, "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," 2020.

[4] P. Mancarella, S. Püschel-Løvengreen, C. Bas-Domenech, and L. Zhang, "Study of advanced modelling for network planning under uncertainty || Part 1: Review of frameworks and industrial practices for decision-making in transmission network planning," 2020.

[5] B. S. Palmintier and M. D. Webster, "Impact of Operational Flexibility on Electricity Generation Planning with Renewable and Carbon Targets," *IEEE Trans Sustain Energy*, vol. 7, no. 2, pp. 672–684, 2016, doi: 10.1109/TSTE.2015.2498640.

[6] J. Ma, V. Silva, R. Belhomme, D. S. Kirschen, and L. F. Ochoa, "Evaluating and planning flexibility in sustainable power systems," *IEEE Trans Sustain Energy*, vol. 4, no. 1, pp. 200–209, 2013, doi: 10.1109/TSTE.2012.2212471.

[7] K. Poncelet, E. Delarue, and W. D'haeseleer, "Unit commitment constraints in long-term planning models: Relevance, pitfalls and the role of assumptions on flexibility," *Appl Energy*, vol. 258, p. 113843, 2020, doi: 10.1016/j.apenergy.2019.113843.

[8] N. Helistö, J. Kiviluoma, H. Holttinen, J. D. Lara, and B. M. Hodge, "Including operational aspects in the planning of power systems with large amounts of variable generation: A review of modeling approaches," *Wiley Interdiscip Rev Energy Environ*, vol. 8, no. 5, 2019, doi: 10.1002/wene.341.

[9] Y. Dvorkin *et al.*, "Co-planning of investments in transmission and merchant energy storage," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 245–256, 2018, doi: 10.1109/TPWRS.2017.2705187.

[10] G. Diaz, A. Inzunza, and R. Moreno, "The importance of time resolution, operational flexibility and risk aversion in quantifying the value of energy storage in long-term energy planning studies," *Renewable and Sustainable Energy Reviews*, vol. 112, pp. 797–812, 2019, doi: 10.1016/j.rser.2019.06.002.

[11] M. Kristiansen, M. Korpås, H. Farahmand, I. Graabak, and P. Härtel, "Introducing system flexibility to a multinational transmission expansion planning model," in *19th Power Systems Computation Conference, PSCC 2016*, IEEE, 2016. doi: 10.1109/PSCC.2016.7540861.

[12] A. Schwele, J. Kazempour, and P. Pinson, “Do unit commitment constraints affect generation expansion planning? A scalable stochastic model,” *Energy Systems*, vol. 11, no. 2, pp. 247–282, 2020, doi: 10.1007/s12667-018-00321-z.

[13] V. Oree, S. Z. Sayed Hassen, and P. J. Fleming, “Generation expansion planning optimisation with renewable energy integration: A review,” *Renewable and Sustainable Energy Reviews*, vol. 69, pp. 790–803, 2017, doi: 10.1016/j.rser.2016.11.120.

[14] N. E. Koltsaklis and A. S. Dagoumas, “State-of-the-art generation expansion planning: A review,” *Appl Energy*, vol. 230, pp. 563–589, 2018, doi: 10.1016/j.apenergy.2018.08.087.

[15] P. V. Gomes and J. T. Saraiva, “State-of-the-art of transmission expansion planning: A survey from restructuring to renewable and distributed electricity markets,” *International Journal of Electrical Power and Energy Systems*, vol. 111, pp. 411–424, 2019, doi: 10.1016/j.ijepes.2019.04.035.

[16] L. Gacitua *et al.*, “A comprehensive review on expansion planning: Models and tools for energy policy analysis,” *Renewable and Sustainable Energy Reviews*, vol. 98, pp. 346–360, 2018, doi: 10.1016/j.rser.2018.08.043.

[17] A. Inzunza, R. Moreno, A. Bernales, and H. Rudnick, “CVaR constrained planning of renewable generation with consideration of system inertial response, reserve services and demand participation,” *Energy Econ*, vol. 59, pp. 104–117, 2016, doi: 10.1016/j.eneco.2016.07.020.

[18] Z. Wang, J. Wang, G. Li, and M. Zhou, “Generation-expansion planning with linearized primary frequency response constraints,” *Global Energy Interconnection*, vol. 3, no. 4, pp. 346–354, 2020.

[19] S. Wogrin, D. Tejada-Arango, S. Delikaraoglou, and A. Botterud, “Assessing the impact of inertia and reactive power constraints in generation expansion planning,” *Appl Energy*, vol. 280, 2020, doi: 10.1016/j.apenergy.2020.115925.

[20] M. Carrion, Y. Dvorkin, and H. Pandzic, “Primary Frequency Response in Capacity Expansion with Energy Storage,” *IEEE Transactions on Power Systems*, vol. 33, no. 2, pp. 1824–1835, 2018, doi: 10.1109/TPWRS.2017.2735807.

[21] K. J. Singh, A. B. Philpott, and R. K. Wood, “Dantzig-Wolfe Decomposition for Solving Multistage Stochastic Capacity-Planning Problems,” *Oper Res*, vol. 57, no. 5, pp. 1271–1286, 2009, doi: 10.1287/opre.1080.0678.

[22] A. Flores-Quiroz, R. Palma-Behnke, G. Zakeri, and R. Moreno, “A column generation approach for solving generation expansion planning problems with high renewable energy penetration,” *Electric Power Systems Research*, vol. 136, pp. 232–241, 2016, doi: 10.1016/j.epsr.2016.02.011.

[23] B. Moya, R. Moreno, S. Püschel-Løvengreen, A. M. Costa, and P. Mancarella, “Uncertainty representation in investment planning of low-carbon power systems,” *Electric Power Systems Research*, vol. 212, p. 108470, Nov. 2022, doi: 10.1016/j.epsr.2022.108470.

[24] C. Saldarriaga-Cortés, H. Salazar, R. Moreno, and G. Jiménez-Estévez, “Stochastic planning of electricity and gas networks: An asynchronous column generation approach,” *Appl Energy*, vol. 233–234, pp. 1065–1077, 2019, doi: 10.1016/j.apenergy.2018.09.148.

[25] S. Wogrin, D. Tejada-Arango, A. Downward, and A. B. Philpott, “Welfare-maximizing transmission capacity expansion under uncertainty,” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 379, no. 2202, Jul. 2021, doi: 10.1098/rsta.2019.0436.

[26] R. Moreno, A. Street, J. M. Arroyo, and P. Mancarella, “Planning low-carbon electricity systems under uncertainty considering operational flexibility and smart grid technologies,” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 375, no. 2100, 2017, doi: 10.1098/rsta.2016.0305.

[27] F. Vanderbeck, “Implementing Mixed Integer Column Generation,” in *Column Generation*, G. Desaulniers, J. Desrosiers, and M. M. Solomon, Eds., Springer Science & Business Media, 2006. doi: 10.1103/PhysRevE.82.046112.

[28] M. E. Lübbecke and J. Desrosiers, “Selected topics in column generation,” *Oper Res*, vol. 53, no. 6, pp. 1007–1023, 2005, doi: 10.1287/opre.1050.0234.

[29] L. M. Rousseau, M. Gendreau, and D. Feillet, “Interior point stabilization for column generation,” *Operations Research Letters*, vol. 35, no. 5, pp. 660–668, 2007, doi: 10.1016/j.orl.2006.11.004.

[30] O. Du Merle, D. Villeneuve, J. Desrosiers, and P. Hansen, “Stabilized column generation,” *Discrete Math*, vol. 194, no. 1–3, pp. 229–237, 1999, doi: 10.1016/S0012-365X(98)00213-1.

[31] CIGRE, “Optimal power system planning under growing uncertainty,” 2019.

[32] Department for Business Energy & Industrial Strategy, “ELECTRICITY The Capacity Market Rules 2014,” London, UK, 2014.

[33] State Power Economic Research Institute, *电网规划设计手册(Grid planning design manual)*, 1st ed. Beijing: China Electric Power Press, 2015.

[34] C. Kang *et al.*, “Optimal power system planning under growing uncertainty,” 2019.

[35] EirGrid, “Tomorrow’s Energy Scenarios 2019 Ireland,” 2019.

[36] M. Doquet, C. Fourment, and J. Roudergues, “Generation & transmission adequacy of large interconnected power systems: A contribution to the renewal of Monte-Carlo approaches,” in *2011 IEEE Trondheim PowerTech*, IEEE, Jun. 2011, pp. 1–6. doi: 10.1109/PTC.2011.6019444.

[37] Réseau de Transport d’Électricité, “Antares-Probabilistic tool for Electric Systems A New Tool for Adequacy Reports and Economic Simulations.” Réseau de Transport d’Électricité, Paris, pp. 1–43, 2016.

[38] NGESO, “Network Options Assessment 2021/22 Refresh,” 2022. Accessed: Sep. 30, 2022. [Online]. Available: https://www.nationalgrideso.com/document/262981/download

[39] NGESO, “Network Options Assessment Methodology Electricity System Operator 2022-2023,” 2022. Accessed: Sep. 30, 2022. [Online]. Available: https://www.nationalgrideso.com/research-publications/network-options-assessment-noa/methodology

[40] NGESO, “FES 2022 Scenario assumptions,” 2022. Accessed: Sep. 30, 2022. [Online]. Available: https://www.nationalgrideso.com/document/263901/download

[41] EirGrid, “Shaping our electricity future,” 2021. Accessed: Sep. 30, 2022. [Online]. Available: https://www.eirgridgroup.com/site-files/library/EirGrid/Shaping_Our_Electricity_Future_Roadmap.pdf

[42] RTE, “Schéma décennal de développement de réseau 2019 - Synthèse – English version,” 2019. Accessed: Sep. 30, 2022. [Online]. Available: https://assets.rte-france.com/prod/public/2020-07/Schéma%20décennal%20de%20développement%20de%20réseau%202019%20-%20Synthèse%20–%20English%20version.pdf

[43] MISO, “MISO’s Renewable Integration Impact Assessment (RIIA) Summary Report,” 2021. Accessed: Sep. 29, 2022. [Online]. Available: https://www.misoenergy.org/planning/policy-studies/Renewable-integration-impact-assessment/#nt=%2Friiatype%3AReport&t=10&p=0&s=Updated&sd=desc

[44] PJM, “Regional Transmission Expansion Plan (RTEP),” 2021. Accessed: Sep. 29, 2022. [Online]. Available: https://www.pjm.com/library/reports-notices/rtep-documents

[45] M. R. Jaske, “CEC Development of Higher Electrification Grid Planning Scenarios,” 2022. Accessed: Sep. 29, 2022. [Online]. Available: http://www.caiso.com/InitiativeDocuments/CECPresentation-2022-2023TransmissionPlanningProcess-Jul62022.pdf

[46] CAISO, “Transmission Economic Assessment Methodology (TEAM),” Nov. 2017. Accessed: Sep. 29, 2022. [Online]. Available: http://www.caiso.com/Documents/TransmissionEconomicAssessmentMethodology-Nov2_2017.pdf

[47] Australian Energy Market Operator (AEMO), “Market Modelling Methodologies,” 2019.

[48] Australian Energy Market Operator (AEMO), “Integrated System Plan 2018,” 2018.

[49] TERNA S.P.A. E GRUPPO TERNA, “Documento metodologico per l’applicazione dell’analisi costi benefici applicata al piano di sviluppo 2019,” 2019.

[50] Swissgrid, “Bericht zum Strategischen Netz 2025,” 2015.

[51] MISO, “MISO Futures Report.” https://www.misoenergy.org/planning/transmission-planning/futures-development/ (accessed Sep. 29, 2022).

[52] MISO, “MTEP21 MISO Transmission Expansion Plan Full Report,” Aug. 2022. Accessed: Sep. 29, 2022. [Online]. Available: https://www.misoenergy.org/planning/planning/previous-mtep-reports/#t=10&p=0&s=FileName&sd=desc

[53] MISO, “MTEP21 Addendum Long Range Transmission Planning Tranche 1,” Sep. 2022. Accessed: Sep. 29, 2022. [Online]. Available: https://www.misoenergy.org/planning/transmission-planning/long-range-transmission-planning/

[54] CAISO, “ISO Board Approved 2021-2022 Transmission Plan,” Mar. 2022.

[55] CAISO, “2022-2023 Transmission Planning Process Unified Planning Assumptions And Study Plan,” Jun. 2022. Accessed: Sep. 29, 2022. [Online]. Available: https://stakeholdercenter.caiso.com/RecurringStakeholderProcesses/2022-2023-Transmission-planning-process

[56] CAISO, “20-Year Transmission Outlook,” May 2022.

[57] Nick Dumitriu and Nicholas Rodak, “Market Efficiency Study Process and RTEP Window Project Evaluation Training,” Oct. 2020. Accessed: Sep. 29, 2022. [Online]. Available: https://www.pjm.com/-/media/planning/rtep-dev/market-efficiency/2020-me-study-process-and-rtep-window-project-evaluation-training.ashx

[58] MISO, “MTEP 18 MISO Transmission Enhancement Plan,” Jul. 2019. Accessed: Sep. 29, 2022. [Online]. Available: https://www.misoenergy.org/planning/planning/previous-mtep-reports/#t=10&p=0&s=FileName&sd=desc

[59] MISO, “MTEP18 Futures Summary of Definitions, Uncertainty Variables, Resource Forecasts, Siting Process and Siting Results,” Jul. 2019. Accessed: Sep. 29, 2022. [Online]. Available: “MTEP18 Futures Summary of Definitions, Uncertainty Variables, Resource Forecasts, Siting Process and Siting Results” (MISO, July 12, 2019), https://www.misoenergy.org/planning/transmission-planning/futures-development/

[60] Jonathan L. Ho *et al.*, “Planning Transmission for Uncertainty: Applications and Lessons for the Western Interconnection,” Jan. 2016. Accessed: Sep. 29, 2022. [Online]. Available: https://www.ethree.com/wp-content/uploads/2017/02/Planning-for-Uncertainty-Final-Report.pdf

[61] B. F. Hobbs *et al.*, “Adaptive Transmission Planning: Implementing a New Paradigm for Managing Economic Risks in Grid Expansion,” *IEEE Power and Energy Magazine*, vol. 14, no. 4, pp. 30–40, Jul. 2016, doi: 10.1109/MPE.2016.2547280.

[62] elia, “PLAN DE DÉVELOPPEMENT FÉDÉRAL DU RÉSEAU DE TRANSPORT 2020-2030,” 2019.

[63] BUNDESNETZAGENTUR, “Genehmigung des Szenariorahmens 2019-2030,” 2018.

[64] EirGrid, “Transmission Development Plan 2018-2027,” 2018.

[65] M. Doquet, R. Gonzalez, S. Lepy, E. Momot, and F. Verrier, “A new tool for adequacy reporting of electric systems: ANTARES,” in *42nd International Conference on Large High Voltage Electric Systems 2008, CIGRE 2008*, 2008.

[66] AEMO, “Integrated System Plan Methodology,” 2021. Accessed: Aug. 10, 2022. [Online]. Available: https://aemo.com.au/-/media/files/major-publications/isp/2021/2021-isp-methodology.pdf?la=en

[67] Z. Bie, Y. Lin, G. Li, and F. Li, “Battling the Extreme: A Study on the Power System Resilience,” *Proceedings of the IEEE*, vol. 105, no. 7, pp. 1253–1266, Jul. 2017, doi: 10.1109/JPROC.2017.2679040.

[68] M. Panteli and P. Mancarella, “Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies,” *Electric Power Systems Research*, vol. 127. Elsevier Ltd, pp. 259–270, Jun. 29, 2015. doi: 10.1016/j.epsr.2015.06.012.

[69] A. Stankovic *et al.*, “Comments on the Definition and Quantification of Resilience IEEE Task Force on Definition and Quantification of Resilience,” 2018.

[70] M. Panteli and P. Mancarella, “The grid: Stronger, bigger, smarter?: Presenting a conceptual framework of power system resilience,” *IEEE Power and Energy Magazine*, vol. 13, no. 3, pp. 58–66, May 2015, doi: 10.1109/MPE.2015.2397334.

[71] Y. Wang, C. Chen, J. Wang, and R. Baldick, “Research on Resilience of Power Systems under Natural Disasters - A Review,” *IEEE Transactions on Power Systems*, vol. 31, no. 2, pp. 1604–1613, Mar. 2016, doi: 10.1109/TPWRS.2015.2429656.

[72] X. Liu, M. Shahidehpour, Z. Li, X. Liu, Y. Cao, and Z. Bie, “Microgrids for Enhancing the Power Grid Resilience in Extreme Conditions,” *IEEE Trans Smart Grid*, vol. 8, no. 2, pp. 589–597, Mar. 2017, doi: 10.1109/TSG.2016.2579999.

[73] M. Panteli, P. Mancarella, D. N. Trakas, E. Kyriakides, and N. D. Hatziargyriou, “Metrics and Quantification of Operational and Infrastructure Resilience in Power Systems,” *IEEE Transactions on Power Systems*, vol. 32, no. 6, pp. 4732–4742, Nov. 2017, doi: 10.1109/TPWRS.2017.2664141.

[74] G. Strbac, D. Kirschen, and R. Moreno, “Reliability Standards for the Operation and Planning of Future Electricity Networks,” *Foundations and Trends® in Electric Energy Systems*, vol. 1, no. 1, pp. 143–219, 2016, doi: 10.1561/3100000001.

[75] S. Espinoza, M. Panteli, P. Mancarella, and H. Rudnick, “Multi-phase assessment and adaptation of power systems resilience to natural hazards,” *Electric Power Systems Research*, vol. 136, pp. 352–361, Jul. 2016, doi: 10.1016/j.epsr.2016.03.019.

[76] H. Zhang, H. Yuan, G. Li, and Y. Lin, “Quantitative resilience assessment under a tri-stage framework for power systems,” *Energies (Basel)*, vol. 11, no. 6, Jun. 2018, doi: 10.3390/en11061427.

[77] M. Panteli, C. Pickering, S. Wilkinson, R. Dawson, and P. Mancarella, “Power System Resilience to Extreme Weather: Fragility Modeling, Probabilistic Impact Assessment, and Adaptation Measures,” *IEEE Transactions on Power Systems*, vol. 32, no. 5, pp. 3747–3757, Sep. 2017, doi: 10.1109/TPWRS.2016.2641463.

[78] S. Espinoza *et al.*, “Seismic resilience assessment and adaptation of the Northern Chilean Power System,” 2017.

[79] M. R. Kelly-Gorham, P. Hines, and I. Dobson, "Using historical utility outage data to compute overall transmission grid resilience," in *Proceedings - International Conference on Modern Electric Power Systems, MEPS 2019*, Institute of Electrical and Electronics Engineers Inc., Sep. 2019. doi: 10.1109/MEPS46793.2019.9395039.

[80] W. Yuan, J. Wang, F. Qiu, C. Chen, C. Kang, and B. Zeng, "Robust Optimization-Based Resilient Distribution Network Planning Against Natural Disasters," *IEEE Trans Smart Grid*, vol. 7, no. 6, pp. 2817–2826, Nov. 2016, doi: 10.1109/TSG.2015.2513048.

[81] S. Ma, B. Chen, and Z. Wang, "Resilience enhancement strategy for distribution systems under extreme weather events," *IEEE Trans Smart Grid*, vol. 9, no. 2, pp. 1442–1451, 2018, doi: 10.1109/TSG.2016.2591885.

[82] N. R. Romero, L. K. Nozick, I. D. Dobson, N. Xu, and D. A. Jones, "Transmission and generation expansion to mitigate seismic risk," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 3692–3701, 2013, doi: 10.1109/TPWRS.2013.2265853.

[83] C. Wang, Y. Hou, F. Qiu, S. Lei, and K. Liu, "Resilience Enhancement with Sequentially Proactive Operation Strategies," *IEEE Transactions on Power Systems*, vol. 32, no. 4, pp. 2847–2857, Jul. 2017, doi: 10.1109/TPWRS.2016.2622858.

[84] D. N. Trakas and N. D. Hatziargyriou, "Optimal Distribution System Operation for Enhancing Resilience Against Wildfires," *IEEE Transactions on Power Systems*, vol. 33, no. 2, pp. 2260–2271, Mar. 2018, doi: 10.1109/TPWRS.2017.2733224.

[85] M. Panteli, D. N. Trakas, P. Mancarella, and N. D. Hatziargyriou, "Boosting the Power Grid Resilience to Extreme Weather Events Using Defensive Islanding," *IEEE Trans Smart Grid*, vol. 7, no. 6, pp. 2913–2922, Nov. 2016, doi: 10.1109/TSG.2016.2535228.

[86] N. Romero, N. Xu, L. K. Nozick, I. Dobson, and D. Jones, "Investment planning for electric power systems under terrorist threat," *IEEE Transactions on Power Systems*, vol. 27, no. 1, pp. 108–116, Feb. 2012, doi: 10.1109/TPWRS.2011.2159138.

[87] H. Nagarajan, E. Yamangil, R. Bent, P. Van Hentenryck, and S. Backhaus, "Optimal Resilient transmission Grid Design," in *19th Power Systems Computation Conference, PSCC 2016*, Institute of Electrical and Electronics Engineers Inc., Aug. 2016. doi: 10.1109/PSCC.2016.7540988.

[88] T. Lagos *et al.*, "Identifying Optimal Portfolios of Resilient Network Investments against Natural Hazards, with Applications to Earthquakes," *IEEE Transactions on Power Systems*, vol. 35, no. 2, pp. 1411–1421, Mar. 2020, doi: 10.1109/TPWRS.2019.2945316.

[89] D. Alvarado, R. Moreno, A. Street, M. Panteli, P. Mancarella, and G. Strbac, "Co-Optimizing Substation Hardening and Transmission Expansion Against Earthquakes: A Decision-Dependent Probability Approach," *IEEE Transactions on Power Systems*, 2022, doi: 10.1109/TPWRS.2022.3180363.

[90] Australian Energy Market Operator, "2022 Integrated System Plan," 2022.

[91] S. E. Hosseini and M. A. Wahid, "Hydrogen production from renewable and sustainable energy resources: Promising green energy carrier for clean development," *Renewable and Sustainable Energy Reviews*, vol. 57, pp. 850–866, 2016, doi: 10.1016/j.rser.2015.12.112.

[92] F. Zhang, P. Zhao, M. Niu, and J. Maddy, “The survey of key technologies in hydrogen energy storage,” *Int J Hydrogen Energy*, vol. 41, no. 33, pp. 14535–14552, 2016, doi: 10.1016/j.ijhydene.2016.05.293.

[93] K. E. Lamb, M. D. Dolan, and D. F. Kennedy, “Ammonia for hydrogen storage; A review of catalytic ammonia decomposition and hydrogen separation and purification,” *Int J Hydrogen Energy*, vol. 44, no. 7, pp. 3580–3593, 2019, doi: 10.1016/j.ijhydene.2018.12.024.

[94] McKinsey & Company, “A Perspective on Hydrogen Investment, Deployment and Cost Competitiveness,” no. February, p. 58, 2021.

[95] M. Lambert, “Hydrogen and decarbonisation of gas: false dawn or silver bullet ?,” *The Oxford Institute for energy studies*, no. March, pp. 1–23, 2020.

[96] IRENA, “HYDROGEN FROM RENEWABLE POWER: TECHNOLOGY OUTLOOK FOR THE ENERGY TRANSITION,” 2018.

[97] C. Graham, P. Hayward, J. Foster, and J. Havas, “GenCost 2021-22,” 2022.

[98] S. De-León Almaraz, C. Azzaro-Pantel, L. Montastruc, and S. Domenech, “Hydrogen supply chain optimization for deployment scenarios in the Midi-Pyrénées region, France,” *Int J Hydrogen Energy*, vol. 39, no. 23, pp. 11831–11845, 2014, doi: 10.1016/j.ijhydene.2014.05.165.

[99] A. Almansoori and A. Betancourt-Torcat, “Design of optimization model for a hydrogen supply chain under emission constraints - A case study of Germany,” *Energy*, vol. 111, pp. 414–429, 2016, doi: 10.1016/j.energy.2016.05.123.

[100] P. Nunes, F. Oliveira, S. Hamacher, and A. Almansoori, “Design of a hydrogen supply chain with uncertainty,” *Int J Hydrogen Energy*, vol. 40, no. 46, pp. 16408–16418, 2015, doi: 10.1016/j.ijhydene.2015.10.015.

[101] M. Reuß, T. Grube, M. Robinius, P. Preuster, P. Wasserscheid, and D. Stolten, “Seasonal storage and alternative carriers: A flexible hydrogen supply chain model,” *Appl Energy*, vol. 200, pp. 290–302, 2017, doi: 10.1016/j.apenergy.2017.05.050.

[102] M. Reuß, T. Grube, M. Robinius, and D. Stolten, “A hydrogen supply chain with spatial resolution: Comparative analysis of infrastructure technologies in Germany,” *Appl Energy*, vol. 247, no. April, pp. 438–453, 2019, doi: 10.1016/j.apenergy.2019.04.064.

[103] G. S. Ogumerem, C. Kim, I. Kesisoglou, N. A. Diangelakis, and E. N. Pistikopoulos, “A multi-objective optimization for the design and operation of a hydrogen network for transportation fuel,” *Chemical Engineering Research and Design*, vol. 131, pp. 279–292, 2018, doi: 10.1016/j.cherd.2017.12.032.

[104] N. Sunny, N. Mac Dowell, and N. Shah, “What is needed to deliver carbon-neutral heat using hydrogen and CCS?,” *Energy Environ Sci*, vol. 13, no. 11, pp. 4204–4224, 2020, doi: 10.1039/d0ee02016h.

[105] L. Li, H. Manier, and M. A. Manier, “Hydrogen supply chain network design: An optimization-oriented review,” *Renewable and Sustainable Energy Reviews*, vol. 103, no. December 2018, pp. 342–360, 2019, doi: 10.1016/j.rser.2018.12.060.

[106] P. E. Dodds and W. McDowall, “A review of hydrogen delivery technologies for energy system models,” 2012.

[107] M. Moreno-Benito, P. Agnolucci, and L. G. Papageorgiou, “Towards a sustainable hydrogen economy: Optimisation-based framework for hydrogen infrastructure development,” *Comput Chem Eng*, vol. 102, pp. 110–127, 2017, doi: 10.1016/j.compchemeng.2016.08.005.

[108] N. Johnson and J. Ogden, “A spatially-explicit optimization model for long-term hydrogen pipeline planning,” *Int J Hydrogen Energy*, vol. 37, no. 6, pp. 5421–5433, 2012, doi: 10.1016/j.ijhydene.2011.08.109.

[109] J. André *et al.*, “Design and dimensioning of hydrogen transmission pipeline networks,” *Eur J Oper Res*, vol. 229, no. 1, pp. 239–251, 2013, doi: 10.1016/j.ejor.2013.02.036.

[110] A. C. Weber and L. G. Papageorgiou, “Design of hydrogen transmission pipeline networks with hydraulics,” *Chemical Engineering Research and Design*, vol. 131, pp. 266–278, 2018, doi: 10.1016/j.cherd.2018.01.022.

[111] S. Samsatli and N. J. Samsatli, “A multi-objective MILP model for the design and operation of future integrated multi-vector energy networks capturing detailed spatio-temporal dependencies,” *Appl Energy*, vol. 220, no. August 2017, pp. 893–920, 2018, doi: 10.1016/j.apenergy.2017.09.055.

[112] L. Welder, D. S. Ryberg, L. Kotzur, T. Grube, M. Robinius, and D. Stolten, “Spatio-temporal optimization of a future energy system for power-to-hydrogen applications in Germany,” *Energy*, vol. 158, pp. 1130–1149, 2018, doi: 10.1016/j.energy.2018.05.059.

[113] S. Samsatli, I. Staffell, and N. J. Samsatli, “Optimal design and operation of integrated wind-hydrogen-electricity networks for decarbonising the domestic transport sector in Great Britain,” *Int J Hydrogen Energy*, vol. 41, no. 1, pp. 447–475, 2016, doi: 10.1016/j.ijhydene.2015.10.032.

[114] L. Welder *et al.*, “Design and evaluation of hydrogen electricity reconversion pathways in national energy systems using spatially and temporally resolved energy system optimization,” *Int J Hydrogen Energy*, vol. 44, no. 19, pp. 9594–9607, 2019, doi: 10.1016/j.ijhydene.2018.11.194.

[115] M. Kim and J. Kim, “An integrated decision support model for design and operation of a wind-based hydrogen supply system,” *Int J Hydrogen Energy*, vol. 42, no. 7, pp. 3899–3915, 2017, doi: 10.1016/j.ijhydene.2016.10.129.

[116] J. Li *et al.*, “Optimal Investment of Electrolyzers and Seasonal Storages in Hydrogen Supply Chains Incorporated with Renewable Electric Networks,” *IEEE Trans Sustain Energy*, vol. 11, no. 3, pp. 1773–1784, 2020, doi: 10.1109/TSTE.2019.2940604.

[117] B. Miao, L. Giordano, and S. H. Chan, “Long-distance renewable hydrogen transmission via cables and pipelines,” *Int J Hydrogen Energy*, vol. 46, no. 36, pp. 18699–18718, 2021, doi: 10.1016/j.ijhydene.2021.03.067.

[118] A. Wang, K. Van der Leun, D. Peters, and M. Buseman, “European Hydrogen Backbone,” no. July, p. 24, 2020.

[119] J. Jens, A. Wang, K. Van der Leun, D. Peters, and M. Buseman, "Extending the European Hydrogen Backbone," *Gas for Climate*, no. April, 2021.

[120] J. D. Rhodes *et al.*, "Renewable Electrolysis in Texas: Pipelines versus Power Lines," 2021.

[121] A. Singlitico, J. Østergaard, and S. Chatzivasileiadis, "Onshore, offshore or in-turbine electrolysis? Techno-economic overview of alternative integration designs for green hydrogen production into Offshore Wind Power Hubs," *Renewable and Sustainable Energy Transition*, vol. 1, p. 100005, 2021, doi: 10.1016/j.rset.2021.100005.

[122] McKinsey & Company, "A Perspective on Hydrogen Investment, Deployment and Cost Competitiveness," no. February, p. 58, 2021.

[123] C. Johnston, M. H. Ali Khan, R. Amal, R. Daiyan, and I. MacGill, "Shipping the sunshine: An open-source model for costing renewable hydrogen transport from Australia," *Int J Hydrogen Energy*, vol. 47, no. 47, pp. 20362–20377, 2022, doi: 10.1016/j.ijhydene.2022.04.156.

[124] S. Mhanna, I. Saedi, G. Liu, and P. Mancarella, "Towards Optimal Integrated Planning of Electricity and Hydrogen Infrastructure for Large-Scale Renewable Energy Transport," in *IREP 2022 Bulk Power Systems Dynamics and Control Symposium*, 2022, pp. 1–12.

[125] F. H. Saadi, N. S. Lewis, and E. W. McFarland, "Relative costs of transporting electrical and chemical energy," *Energy Environ Sci*, vol. 11, no. 3, pp. 469–475, 2018, doi: 10.1039/c7ee01987d.

[126] D. DeSantis, B. D. James, C. Houchins, G. Saur, and M. Lyubovsky, "Cost of long-distance energy transmission by different carriers," *iScience*, vol. 24, no. 12, p. 103495, 2021, doi: 10.1016/j.isci.2021.103495.

[127] S. Püschel-Løvengreen, "Security-constrained expansion planning of low carbon power systems," 2021. Accessed: Aug. 03, 2022. [Online]. Available: https://minerva-access.unimelb.edu.au/bitstreams/1adf4b89-d069-5214-b4fa-3e58b2019516/download

[128] P. Mancarella, S. Püschel-Løvengreen, L. Zhang, and C. Bas-Domenech, "Study of advanced modelling for network planning under uncertainty Part 1: Review of frameworks and industrial practices for decision-making in transmission network planning Report prepared for National Grid Electricity System Operator," 2020.

[129] L. Zhang, T. Capuder, and P. Mancarella, "Unified Unit Commitment Formulation and Fast Multi-Service LP Model for Flexibility Evaluation in Sustainable Power Systems," *IEEE Trans Sustain Energy*, vol. 7, no. 2, pp. 658–671, 2016, doi: 10.1109/TSTE.2015.2497411.

[130] S. Püschel-Løvengreen, M. Ghazavi Dozein, S. Low, and P. Mancarella, "Separation event-constrained optimal power flow to enhance resilience in low-inertia power systems," *Electric Power Systems Research*, vol. 189, pp. 1–8, 2020, doi: 10.1016/j.epsr.2020.106678.

[131] Gurobi Optimization LLC, "Gurobi Optimizer Reference Manual." 2021.

[132] L. Wolsey, *Integer Programming*. Wiley, 2020. doi: 10.1002/9781119606475.

[133] A. J. Conejo, M. Carrion, and J. M. Morales, *Decision Making Under Uncertainty in Electricity Markets*. New York: Springer, 2010. doi: 10.1007/978-1-4419-7421-1.

[134] GPA Engineering, "Final Report Pipelines vs Powerlines-A Technoeconomic Analysis in the Australian Context," 2022. [Online]. Available: https://www.energy.gov.au/sites/default/files/Australian%20Energy%20Statistics%202021%20Energy%20Upd

[135] S. Mhanna, I. Saedi, G. Liu, and P. Mancarella, "Towards Optimal Integrated Planning of Electricity and Hydrogen Infrastructure for Large-Scale Renewable Energy Transport," in *IREP 2022 Bulk Power Systems Dynamics and Control Symposium*, Jul. 2022, pp. 1–12. [Online]. Available: http://arxiv.org/abs/2207.03567

[136] D. DeSantis, B. D. James, C. Houchins, G. Saur, and M. Lyubovsky, "Cost of long-distance energy transmission by different carriers," *iScience*, vol. 24, no. 12, Dec. 2021, doi: 10.1016/j.isci.2021.103495.

[137] I. J. Scott, P. M. S. Carvalho, A. Botterud, and C. A. Silva, "Clustering representative days for power systems generation expansion planning: Capturing the effects of variable renewables and energy storage," *Appl Energy*, vol. 253, 2019, doi: 10.1016/j.apenergy.2019.113603.

Appendix A: Representation of operation

The following table presents the specific weeks used to represent the operation in each of the nodes considered in this study. The ISP 2022 [1] database is publicly available and all the time-varying data points have a timestamp. The representative weeks presented below specify the start date and time, and the end date and time. All demand and VRE profiles used to run the different case study applications across this study can be reconstructed using the data of Table A.0.1.

Table A.0.1. Operational conditions represented in each of the nodes of the scenario tree

NODE	SCENARIO	DATE START	DATE END
1	Step	8/8/2022 0:00	14/8/2022 23:00
1	Step	12/9/2022 0:00	18/9/2022 23:00
1	Step	29/8/2022 0:00	4/9/2022 23:00
1	Step	2/5/2022 0:00	8/5/2022 23:00
1	Step	14/11/2022 0:00	20/11/2022 23:00
1	Step	24/10/2022 0:00	30/10/2022 23:00
2	Slow	14/11/2027 0:00	20/11/2027 23:00
2	Slow	4/4/2027 0:00	10/4/2027 23:00
2	Slow	18/7/2027 0:00	24/7/2027 23:00
2	Slow	17/10/2027 0:00	23/10/2027 23:00
2	Slow	24/10/2027 0:00	30/10/2027 23:00
2	Slow	2/5/2027 0:00	8/5/2027 23:00
3	Progressive	4/7/2027 0:00	10/7/2027 23:00
3	Progressive	6/6/2027 0:00	12/6/2027 23:00
3	Progressive	8/8/2027 0:00	14/8/2027 23:00
3	Progressive	13/6/2027 0:00	19/6/2027 23:00
3	Progressive	28/2/2027 0:00	6/3/2027 23:00
3	Progressive	21/2/2027 0:00	27/2/2027 23:00
4	Step	12/9/2027 0:00	18/9/2027 23:00
4	Step	16/5/2027 0:00	22/5/2027 23:00
4	Step	14/11/2027 0:00	20/11/2027 23:00
4	Step	14/3/2027 0:00	20/3/2027 23:00
4	Step	6/6/2027 0:00	12/6/2027 23:00
4	Step	28/11/2027 0:00	4/12/2027 23:00
5	H2 Superpower	19/9/2027 0:00	25/9/2027 23:00
5	H2 Superpower	28/2/2027 0:00	6/3/2027 23:00
5	H2 Superpower	7/2/2027 0:00	13/2/2027 23:00
5	H2 Superpower	14/3/2027 0:00	20/3/2027 23:00
5	H2 Superpower	21/2/2027 0:00	27/2/2027 23:00
5	H2 Superpower	4/7/2027 0:00	10/7/2027 23:00
6	Slow	6/3/2032 0:00	12/3/2032 23:00
6	Slow	20/3/2032 0:00	26/3/2032 23:00
6	Slow	24/7/2032 0:00	30/7/2032 23:00
6	Slow	27/11/2032 0:00	3/12/2032 23:00
6	Slow	27/3/2032 0:00	2/4/2032 23:00
6	Slow	17/1/2032 0:00	23/1/2032 23:00
7	Progressive	9/10/2032 0:00	15/10/2032 23:00
7	Progressive	7/8/2032 0:00	13/8/2032 23:00
7	Progressive	11/9/2032 0:00	17/9/2032 23:00
7	Progressive	19/6/2032 0:00	25/6/2032 23:00
7	Progressive	25/9/2032 0:00	1/10/2032 23:00
7	Progressive	12/6/2032 0:00	18/6/2032 23:00
8	Step	27/3/2032 0:00	2/4/2032 23:00
8	Step	17/7/2032 0:00	23/7/2032 23:00
8	Step	9/10/2032 0:00	15/10/2032 23:00
8	Step	15/5/2032 0:00	21/5/2032 23:00
8	Step	28/8/2032 0:00	3/9/2032 23:00
8	Step	4/12/2032 0:00	10/12/2032 23:00
9	Progressive	9/10/2032 0:00	15/10/2032 23:00
9	Progressive	7/8/2032 0:00	13/8/2032 23:00
9	Progressive	11/9/2032 0:00	17/9/2032 23:00
9	Progressive	19/6/2032 0:00	25/6/2032 23:00
9	Progressive	25/9/2032 0:00	1/10/2032 23:00

NODE	SCENARIO	DATE START	DATE END
17	Step	21/3/2037 0:00	27/3/2037 23:00
17	Step	12/12/2037 0:00	18/12/2037 23:00
17	Step	21/11/2037 0:00	27/11/2037 23:00
17	Step	28/11/2037 0:00	4/12/2037 23:00
17	Step	19/12/2037 0:00	25/12/2037 23:00
17	Step	15/8/2037 0:00	21/8/2037 23:00
18	Progressive	31/1/2037 0:00	6/2/2037 23:00
18	Progressive	26/9/2037 0:00	2/10/2037 23:00
18	Progressive	10/10/2037 0:00	16/10/2037 23:00
18	Progressive	13/6/2037 0:00	19/6/2037 23:00
18	Progressive	11/4/2037 0:00	17/4/2037 23:00
18	Progressive	22/8/2037 0:00	28/8/2037 23:00
19	Step	21/3/2037 0:00	27/3/2037 23:00
19	Step	12/12/2037 0:00	18/12/2037 23:00
19	Step	21/11/2037 0:00	27/11/2037 23:00
19	Step	28/11/2037 0:00	4/12/2037 23:00
19	Step	19/12/2037 0:00	25/12/2037 23:00
19	Step	15/8/2037 0:00	21/8/2037 23:00
20	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
20	H2 Superpower	11/7/2037 0:00	17/7/2037 23:00
20	H2 Superpower	24/1/2037 0:00	30/1/2037 23:00
20	H2 Superpower	5/9/2037 0:00	11/9/2037 23:00
20	H2 Superpower	15/8/2037 0:00	21/8/2037 23:00
20	H2 Superpower	5/12/2037 0:00	11/12/2037 23:00
21	Step	21/3/2037 0:00	27/3/2037 23:00
21	Step	12/12/2037 0:00	18/12/2037 23:00
21	Step	21/11/2037 0:00	27/11/2037 23:00
21	Step	28/11/2037 0:00	4/12/2037 23:00
21	Step	19/12/2037 0:00	25/12/2037 23:00
21	Step	15/8/2037 0:00	21/8/2037 23:00
22	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
22	H2 Superpower	11/7/2037 0:00	17/7/2037 23:00
22	H2 Superpower	24/1/2037 0:00	30/1/2037 23:00
22	H2 Superpower	5/9/2037 0:00	11/9/2037 23:00
22	H2 Superpower	15/8/2037 0:00	21/8/2037 23:00
22	H2 Superpower	5/12/2037 0:00	11/12/2037 23:00
23	Progressive	31/1/2037 0:00	6/2/2037 23:00
23	Progressive	26/9/2037 0:00	2/10/2037 23:00
23	Progressive	10/10/2037 0:00	16/10/2037 23:00
23	Progressive	13/6/2037 0:00	19/6/2037 23:00
23	Progressive	11/4/2037 0:00	17/4/2037 23:00
23	Progressive	22/8/2037 0:00	28/8/2037 23:00
24	Step	21/3/2037 0:00	27/3/2037 23:00
24	Step	12/12/2037 0:00	18/12/2037 23:00
24	Step	21/11/2037 0:00	27/11/2037 23:00
24	Step	28/11/2037 0:00	4/12/2037 23:00
24	Step	19/12/2037 0:00	25/12/2037 23:00
24	Step	15/8/2037 0:00	21/8/2037 23:00
25	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
25	H2 Superpower	11/7/2037 0:00	17/7/2037 23:00
25	H2 Superpower	24/1/2037 0:00	30/1/2037 23:00
25	H2 Superpower	5/9/2037 0:00	11/9/2037 23:00
25	H2 Superpower	15/8/2037 0:00	21/8/2037 23:00

9	Progressive	12/6/2032 0:00	18/6/2032 23:00	25	H2 Superpower	5/12/2037 0:00	11/12/2037 23:00
10	Step	27/3/2032 0:00	2/4/2032 23:00	26	Step	21/3/2037 0:00	27/3/2037 23:00
10	Step	17/7/2032 0:00	23/7/2032 23:00	26	Step	12/12/2037 0:00	18/12/2037 23:00
10	Step	9/10/2032 0:00	15/10/2032 23:00	26	Step	21/11/2037 0:00	27/11/2037 23:00
10	Step	15/5/2032 0:00	21/5/2032 23:00	26	Step	28/11/2037 0:00	4/12/2037 23:00
10	Step	28/8/2032 0:00	3/9/2032 23:00	26	Step	19/12/2037 0:00	25/12/2037 23:00
10	Step	4/12/2032 0:00	10/12/2032 23:00	26	Step	15/8/2037 0:00	21/8/2037 23:00
11	H2 Superpower	14/2/2032 0:00	20/2/2032 23:00	27	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
11	H2 Superpower	27/11/2032 0:00	3/12/2032 23:00	27	H2 Superpower	11/7/2037 0:00	17/7/2037 23:00
11	H2 Superpower	18/9/2032 0:00	24/9/2032 23:00	27	H2 Superpower	24/1/2037 0:00	30/1/2037 23:00
11	H2 Superpower	4/12/2032 0:00	10/12/2032 23:00	27	H2 Superpower	5/9/2037 0:00	11/9/2037 23:00
11	H2 Superpower	22/5/2032 0:00	28/5/2032 23:00	27	H2 Superpower	15/8/2037 0:00	21/8/2037 23:00
11	H2 Superpower	28/2/2032 0:00	5/3/2032 23:00	27	H2 Superpower	5/12/2037 0:00	11/12/2037 23:00
12	Step	27/3/2032 0:00	2/4/2032 23:00	28	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
12	Step	17/7/2032 0:00	23/7/2032 23:00	28	H2 Superpower	11/7/2037 0:00	17/7/2037 23:00
12	Step	9/10/2032 0:00	15/10/2032 23:00	28	H2 Superpower	24/1/2037 0:00	30/1/2037 23:00
12	Step	15/5/2032 0:00	21/5/2032 23:00	28	H2 Superpower	5/9/2037 0:00	11/9/2037 23:00
12	Step	28/8/2032 0:00	3/9/2032 23:00	28	H2 Superpower	15/8/2037 0:00	21/8/2037 23:00
12	Step	4/12/2032 0:00	10/12/2032 23:00	28	H2 Superpower	5/12/2037 0:00	11/12/2037 23:00
13	H2 Superpower	14/2/2032 0:00	20/2/2032 23:00	29	Step	21/3/2037 0:00	27/3/2037 23:00
13	H2 Superpower	27/11/2032 0:00	3/12/2032 23:00	29	Step	12/12/2037 0:00	18/12/2037 23:00
13	H2 Superpower	18/9/2032 0:00	24/9/2032 23:00	29	Step	21/11/2037 0:00	27/11/2037 23:00
13	H2 Superpower	4/12/2032 0:00	10/12/2032 23:00	29	Step	28/11/2037 0:00	4/12/2037 23:00
13	H2 Superpower	22/5/2032 0:00	28/5/2032 23:00	29	Step	19/12/2037 0:00	25/12/2037 23:00
13	H2 Superpower	28/2/2032 0:00	5/3/2032 23:00	29	Step	15/8/2037 0:00	21/8/2037 23:00
14	H2 Superpower	14/2/2032 0:00	20/2/2032 23:00	30	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
14	H2 Superpower	27/11/2032 0:00	3/12/2032 23:00	30	H2 Superpower	11/7/2037 0:00	17/7/2037 23:00
14	H2 Superpower	18/9/2032 0:00	24/9/2032 23:00	30	H2 Superpower	24/1/2037 0:00	30/1/2037 23:00
14	H2 Superpower	4/12/2032 0:00	10/12/2032 23:00	30	H2 Superpower	5/9/2037 0:00	11/9/2037 23:00
14	H2 Superpower	22/5/2032 0:00	28/5/2032 23:00	30	H2 Superpower	15/8/2037 0:00	21/8/2037 23:00
14	H2 Superpower	28/2/2032 0:00	5/3/2032 23:00	30	H2 Superpower	5/12/2037 0:00	11/12/2037 23:00
15	Slow	26/9/2037 0:00	2/10/2037 23:00	31	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
15	Slow	24/10/2037 0:00	30/10/2037 23:00	31	H2 Superpower	11/7/2037 0:00	17/7/2037 23:00
15	Slow	19/12/2037 0:00	25/12/2037 23:00	31	H2 Superpower	24/1/2037 0:00	30/1/2037 23:00
15	Slow	26/9/2037 0:00	2/10/2037 23:00	31	H2 Superpower	5/9/2037 0:00	11/9/2037 23:00
15	Slow	15/8/2037 0:00	21/8/2037 23:00	31	H2 Superpower	15/8/2037 0:00	21/8/2037 23:00
15	Slow	10/1/2037 0:00	16/1/2037 23:00	31	H2 Superpower	5/12/2037 0:00	11/12/2037 23:00
16	Progressive	31/1/2037 0:00	6/2/2037 23:00	32	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
16	Progressive	26/9/2037 0:00	2/10/2037 23:00	32	H2 Superpower	11/7/2037 0:00	17/7/2037 23:00
16	Progressive	10/10/2037 0:00	16/10/2037 23:00	32	H2 Superpower	24/1/2037 0:00	30/1/2037 23:00
16	Progressive	13/6/2037 0:00	19/6/2037 23:00	32	H2 Superpower	5/9/2037 0:00	11/9/2037 23:00
16	Progressive	11/4/2037 0:00	17/4/2037 23:00	32	H2 Superpower	15/8/2037 0:00	21/8/2037 23:00
16	Progressive	22/8/2037 0:00	28/8/2037 23:00	32	H2 Superpower	5/12/2037 0:00	11/12/2037 23:00

Appendix B: Representation of operation for resilience case study application

The following table presents the specific weeks used to represent the operation in each of the nodes of the resilience study application.

Table B.0.1. Operational conditions represented in each of the nodes of the scenario tree for the resilience case study.

NODE	SCENARIO	DATE START	DATE END
1	Step	8/8/2022 0:00	14/8/2022 23:00
2	Slow	14/11/2027 0:00	20/11/2027 23:00
3	Progressive	4/7/2027 0:00	10/7/2027 23:00
4	Step	12/9/2027 0:00	18/9/2027 23:00
5	H2 Superpower	19/9/2027 0:00	25/9/2027 23:00
6	Slow	6/3/2032 0:00	12/3/2032 23:00
7	Progressive	9/10/2032 0:00	15/10/2032 23:00
8	Step	27/3/2032 0:00	2/4/2032 23:00
9	Progressive	9/10/2032 0:00	15/10/2032 23:00
10	Step	27/3/2032 0:00	2/4/2032 23:00
11	H2 Superpower	14/2/2032 0:00	20/2/2032 23:00
12	Step	27/3/2032 0:00	2/4/2032 23:00
13	H2 Superpower	14/2/2032 0:00	20/2/2032 23:00
14	H2 Superpower	14/2/2032 0:00	20/2/2032 23:00
15	Slow	26/9/2037 0:00	2/10/2037 23:00
16	Progressive	31/1/2037 0:00	6/2/2037 23:00
17	Step	21/3/2037 0:00	27/3/2037 23:00
18	Progressive	31/1/2037 0:00	6/2/2037 23:00
19	Step	21/3/2037 0:00	27/3/2037 23:00
20	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
21	Step	21/3/2037 0:00	27/3/2037 23:00
22	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
23	Progressive	31/1/2037 0:00	6/2/2037 23:00
24	Step	21/3/2037 0:00	27/3/2037 23:00
25	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
26	Step	21/3/2037 0:00	27/3/2037 23:00
27	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
28	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
29	Step	21/3/2037 0:00	27/3/2037 23:00
30	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
31	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00
32	H2 Superpower	20/6/2037 0:00	26/6/2037 23:00

Appendix C: Cost and technical assumptions of hydrogen pipelines, HVAC links, and HVDC links in Section 7.

To demonstrating the capabilities of the modelling in Section 7, this appendix lists the assumptions on input technical parameters and costs of hydrogen pipeline links, HVAC links, and HVDC links. These are obtained from various reliable publicly available sources, including AEMO [1] and the peak body representing Australian pipeline infrastructure [134].

Table C.0.1. Cost and technical assumptions for HVAC systems [1]

Option	Voltage (kV)	Circuits	OHL cost (MAUD/km)	Capacity (MVA)	Substation 1 cost (MAUD)	Substation 2 cost (MAUD)
1	500	Double	3.747	6080	178.5	172.2
2	500	Single	2.907	2900	107.9	107.9
3	330	Double	2.839	2400	89.7	89.7
4	275	Double	2.205	1900	78.9	54.0
5	330	Single	2.041	1000	45.8	45.8
6	275	Single	1.717	536	26.0	26.0
7	132	Single	1.241	169	12.3	12.3

Table C.0.2. Cost and technical assumptions for HVDC systems [1]

Option	Voltage (kV)	Subcategory	Capacity (MW)	OHL cost (MAUD/km)	Converter station 1 cost (MAUD)	Converter station 2 cost (MAUD)
1	±320	HVDC - VSC	1500	1.99	474.68	357.82
2	±500	HVDC - VSC	2000	2.54	507.37	509.20

Table C.0.3. Cost and technical assumptions for hydrogen pipelines [134], where D_n is the nominal diameter of the pipe

Option	D_n (mm)	D_n (inch)	Minimum pressure (MPa)	Maximum pressure (MPa)	Cost (USD/Tonne)
1	100	4	3	12	2873.5
2	150	6	3	12	2873.5
3	200	8	3	12	2873.5
4	250	10	3	12	2873.5
5	300	12	3	12	2873.5
6	350	14	3	12	2873.5
7	400	16	3	12	2873.5
8	450	18	3	12	2873.5
9	500	20	3	12	2873.5
10	550	22	3	12	2873.5
11	600	24	3	12	2873.5
12	650	26	3	12	2873.5
13	700	28	3	12	2873.5
14	750	30	3	12	2873.5
15	800	32	3	12	2873.5
16	850	34	3	12	2873.5
17	900	36	3	12	2873.5
18	950	38	3	12	2873.5
19	1000	40	3	12	2873.5
20	1050	42	3	12	2873.5
21	1100	44	3	12	2873.5
22	1150	46	3	12	2873.5

Appendix D: Resilience Expansion Planning (EPRI)

Resilience Expansion Planning

Review of Industry Practices and Model Development

Jesse Bukenberger, Miguel Ortega-Vazquez

Contents

Introduction

Resilience in the Electricity Sector

Resilience has always been essential for maintaining reliable power system operations, but as the grid faces multifaceted uncertainty and a changing climate, resilience is becoming a central component of grid planning. Planners increasingly must anticipate and prepare for hazardous conditions in the distant future; both foresight and flexibility are needed to ensure that the systems that generate and deliver electricity are protected against emerging threats.

Resilience is often defined as the ability to withstand and recover from disruption, but more often resilience primarily refers to high-impact events that go beyond normal, and random, contingencies. Such resilience risks often come from natural disasters and extreme weather events, but resilience also encompasses human-caused disruptions such as cyberattack, and potentially disruptive societal shifts and public policy goals such as the transition to an electrified energy sector with high renewable energy penetration.

To address the increasing risks of damages and disruption, resilience considerations should be considered early in the planning process and ideally would be integrated directly into capacity planning models. These resilience considerations include the potential for hazardous conditions and events, the vulnerability of infrastructure to these hazards, the adaptation options available for protecting against or avoiding these hazards, and the consequences—to the grid and to society—of leaving threats unmitigated.

Resilience Goals for Capacity Expansion Planners

Resilience planning is, of course, a much larger topic than what capacity planners alone can answer, and a narrower focus is needed. The US Department of Energy lays out a helpful resilience planning framework [2]. The framework can be summarized with five steps: scoping the problem, collecting data, conducting a vulnerability assessment, resilience planning, and revisit and update assumptions. The larger effort likely falls in the data collection and vulnerability assessment steps.

Before any capacity planning efforts, a tremendous data collection task is required. For a climate focused study, this involves developing climate scenarios for the system's region and downscaling the climate scenario model into weather parameters that are relevant. The vulnerability assessment involves mapping the projected weather data onto the system components, identifying any risks, and identifying possible adaptation options [3]. At this point capacity planners can build weather events and projections into planning models along with component risks, adaptation options, and any performance implications.

The capacity planner's role in resilience planning is to identify the least cost expansion plans and adaptation options that meet the system loads and maintain an acceptable risk of disruption during extreme events. Systemic risks of all types can often be mitigated by designing a system with diversified vulnerabilities and sufficient redundancies. Capacity planning tools have the potential to find resilient expansion strategies without excessive cost, by taking advantage of these risk mitigation principles.

This Report

While the focus of this report is on transmission capacity planning, we will consider generation expansion planning in similar detail. A major component of resilience planning is determining which resilience options are most cost effective. The question of whether resilience comes from transmission investments or from something on the generator side is central to resilience planning. Thus, both generation and transmission are important to consider together [4].

This report briefly reviews resilience planning practices in the United States, as well as some academic and industry research. The aim is not to be exhaustive but to highlight the more exemplary work, the current challenges, and any gaps between research and practices. Another aim of this report is to collect some approaches that can be implemented immediately to improve industry practice without significant barriers. Several of these methods will be demonstrated on a toy system to clarify ambiguities and to demonstrate the possible insights that can be obtained.

Review of Resilience Planning Practices and Research

Utilities

Resilience planning at utilities is varied, and in many cases, quite sophisticated. Efforts are primarily focused on hazard characterization and vulnerability assessments for the assets within the utility's footprint. These studies consider a broad range of hazards that exist today and those that are anticipated to worsen with climate change [5] [6]. For example, Seattle City Light identifies sea level rise, extreme temperature, wind, wildfire, landslide, and stream overflow flooding as risks to transmission infrastructure in its service area [7].

While high-impact events are not integrated directly into utilities' integrated resource plans (IRP), scenarios representing climate temperature extremes often are. High-impact events are usually considered alongside the IRP or as part of a separate resilience adaptation plan. These adaptation plans usually follow the DoE guidelines of determining whether an asset is critical to grid operations, assessing its vulnerability, and considering adaptation options.

Tennessee valley authority brings a climate change scenario into its IRP, but finds primarily that winter and nighttime warming will ultimately reduce peak loads by 2% while increasing energy demand by 1% overall [8]. While TVA's separate climate change adaptation plan, discusses hazards such as flood and drought [9].

ConEdison's climate scenarios forecast more substantial summer peak temperature increases along with transmission deratings [10]. ConEdison also considers several operational changes, storm hardening investments, and flexibility investments aimed specifically at reducing the impact to customers most vulnerable during storms [11].

PacifiCorp also includes a climate change scenario in the formal IRP, but the analysis finds that energy demand will fall, as will winter peaks, with small increases in summer peaks. A separate part of the report finds that generators, especially remote renewable generators and hydro generators are at risk from wildfires due to the transmission needed to access the remote locations. These risks are to be addressed by gradually updating line infrastructure to reduce ignition risk [12].

The small footprint of some utilities allows for more detailed studies. For example, an Entergy study focuses on hurricanes, sea level rise, and land subsidence hazards on a small region of the gulf coast. The researchers develop projections for how hurricane severity will worsen in three scenarios developed for the study [13].

Another small footprint utility, San Diego Gas and Electric uses a flexible adaptation pathways approach that resembles a decision tree. The utility planner's immediate actions will ultimately reduce the cost of adaptation options if and when they are needed in the future. The immediate actions include enhancing storm modeling and datasets, research into thresholds that could trigger investments (for example clearing a regulatory restriction in investments), and real option analysis to value candidate projects. These immediate actions will eventually improve decisions as to which grid enhancements and hardening investments are necessary and which actions will be most effective options [14].

Southern California Edison tool Cal-Adapt provides detailed mapping of hazard risks and severity including extreme temperatures, precipitation, sea level rise, wind, and wildfire. The tool helps identify at-risk assets and the locations that need mitigating actions. For example, one finding is that coincident heat and fire events pose a credible risk as extreme heat can destabilize the grid at the same time wildfires near intertie lines prevent imports. While the coincident hazards are unlikely, the event is credible and would have a high impact. SCE explores several adaptation investments including system redundancies, and fire resistant hardening investments [15].

ISO/RTO Transmission Planners

ISO/RTO, take a more systemic approach to investment planning and in some instances integrate resilience considerations into their planning practices. Often these studies are focused on a particular hazard or risk, and often in response to a recent disruption. The most advanced work is aimed at studying transitions to highly electrified energy sectors with high renewable penetrations. Other simpler considerations include running sensitivities for security by running sensitivity scenarios with high gas prices and disruptive events like fires in dense areas.

The resilience studies are often standalone sensitivity studies that are not necessarily integrated into a capacity planning model. While transmission planners know that there are systemic risks that could be addressed with large scale TEP investments more efficiently, there is lack a tractable process for doing so and quantifying the benefits [16], [17].

California ISO CAISO, conducts its normal planning cycle, which looks out 10 years and includes special studies of resilience considerations such as wildfires, fuel security, or the retirements of large generators [18]. In addition, California initiated a 20 year transmission plan in response to SB100 to study how the state can meet the decarbonization policies required by recent public policy [19]. This work includes developing electrification scenarios which in turn impact the load magnitude and shape [20].

MISO renewable integration impact assessment (RIIA) [21] explores the impacts on increasing renewable penetrations and finds the important and stressful operating conditions shift and amplify as renewable penetrations increase. MISO also has its own set of detailed scenarios, which describe different resource mixes over the next twenty years as the energy system transitions to a low carbon, electrified system at different rates [22]. MISO makes use of these scenarios and a least regrets approach to develop its long-range transmission plan with investments that are valuable under any of the scenarios [23].

PJM discusses resilience opportunities more directly in its regional planning report than most planners [24], noting the conditions that stress resilience, possible tools to enhance resilience, and discussing metrics for evaluating resilience. PJM studies scenarios for fuel prices and load sensitivities [25].

The western electricity coordinating council (WECC) also develops scenarios and monitors risk ten years into the future in support of other entities such as CAISO [26]. WECC has, in the past, also collaborated with academic institutions to conduct stochastic expansion modeling that is not typically done by system planners [27].

Labs and industry research

Industry focused research for resilience planning is largely preliminary and at an exploratory stage.

This research helps to see where the industry sees resilience planning challenges. A major focus is around high-impact events: how to generate credible common mode events for a future climate, which events are most important to consider [28] [29], metrics for quantifying risk and performance of the system in extreme events [30] [31], and how to differentiate between normal conditions and high-impact, low-frequency events, and ongoing adverse events such as persistent drought [32].

Academia

While academic work has not explicitly used the resilience planning label, several studies have explored how disruptive events and uncertain long-term futures can inform planning decisions.

One avenue of research has confirmed that confronting long-term uncertainty directly in transmission planning problems is important both to avoid making maladaptive investments in the near term, and to appropriately value investments that provide the flexibility to transition to many futures [33]. More recent work has reiterates that increased representation of long-term uncertainty is one of the more valuable enhancements than can be made to transmission capacity planning models [34]. And [35] demonstrate that there are several long-term strategies that would be optimal under different scenarios, but picking the investments to make now is not possible with several individual scenario optimizations.

However, the methods for finding these adaptable plans, stochastic optimization, are too computationally taxing to use for more detailed planning studies. In response, iterative refinement methods have been developed to reduce, or at least distribute, this computational burden including Benders decomposition [36] and progressive hedging [37]. An alternative approach to making stochastic models tractable, focuses instead on selecting a few important scenarios [38], or grouping like scenarios together [39].

Most scenario selection methods can apply to shorter timeframes equally well. And methods originally developed to select important scenarios and operating conditions can be adapted to selecting important extreme events for resilience planning. For example the ALFA method in [40] and [41] has been successfully adapted to identifying extreme disruptions [42].

Methods for Integrating Resilience into Capacity Planning Models

Capacity Expansion Planning Formulation

We present a generic capacity expansion planning formulation here to later demonstrate how extreme events and hardening investments can be included in the model.

Sets and indices

$b \in B$ Buses

$l \in L$ Lines

$l \in L_b^{In}$ Lines oriented with positive flow going into bus b

$l \in L_b^{Out}$ Lines oriented with positive flow leaving bus b

$g \in G$ Generators

$g \in G_b$ Generators at bus b

$g \in G^{RE}$ Renewable generators

$g \in G^S$ Storage units

$t \in T$ Investment stages

$m \in M$ Time blocks (e.g. Representative days)

$h \in H_m$ Hours in block m, also let $h = 1, \dots, H_m$

Parameters

c_{lt}^x Line investment costs at each stage

c_{gt}^y Generator investment costs at each stage

c_g^F Fixed generator costs

c_{gtmh}^V Variable maintenance, operations, and fuel costs

c^u Value of lost load (VoLL)

ζ_t Discounting factor for stage

w_m Weight for time blocks, e.g. for a model with four representative days $w_m = \frac{8{,}760}{4*24} = 91.25\ \forall m$

d_{btmh} Demand

D_t Peak demand for planning reserve margin

σ_{gt} Planning reserve margin capacity credit

PRM Planning Reserve Margin

ρ_{gtmh} Renewable capacity factor

λ_g^+, λ_g^- Rate of storage charge/discharge

η_g^+, η_g^- Storage efficiency

e_{gtmh} emissions from generator operations

$\bar{e}_t$ Emissions limits

$\bar{x}_{lt}$ Line investment limits at each stage

$\bar{X}_{lt}$ Total capacity limit for each transmission corridor

X_{l0} Initial line capacity

$\bar{y}_{gt}, \underline{y}_{gt}$ Generator investment upper and lower limits at each stage

$\bar{y}_{gt}^r, \underline{y}_{gt}^r$ Generator retirement upper and lower limits at each stage

$\bar{Y}_{gt}, \underline{Y}_{gt}$ Generator total capacity upper and lower limits at each stage

Y_{g0} Initial generator capacity

$\underline{p}_g$ Generator p-min value

Variables

x_{lt} Line investments in each stage

X_{lt} Cumulative line capacity

y_{gt} Generator investments in each stage

y_{gt}^r Generator retirements in each stage

Y_{gt} Cumulative generator capacity

f_{ltmh} Power flow over line

p_{gtmh} Power output from generator

q_{gtmh}^+ Storage charging

q_{gtmh}^- Storage discharging

Q_{gtmh} Storage state of charge

u_{btmh} Unmet demand at bus

The objective of the model is to minimize the long-term costs of providing adequate service. This includes transmission investment costs, generation investment costs, and fixed generation costs, given in (1), as well as variable operation costs and penalties for unmet demand, given in (2). These components are combined and discounted into a net present value in (3).

$$INV_t = \sum_l c_{lt}^x x_{lt} + \sum_g \left(c_{gt}^y y_{gt} + c_g^F Y_{gt}\right) \tag{1}$$

$$OPS_t = \sum_m w_m \sum_{h\in H_m} \sum_g c_{gtmh}^V p_{gtmh} + \sum_b c^u u_{btmh} \tag{2}$$

$$\min \sum_{t\in T} \gamma_t [INV_t + OPS_t] \tag{3}$$

s.t.

$$x_{lt} \le \bar{x}_{lt}, \quad \forall l, t \tag{4}$$

$$X_{lt} = X_{l0} + \sum_{t'=1}^{t} x_{lt'}, \quad \forall l, t \tag{5}$$

$$X_{lt} \le \bar{X}_{lt}, \quad \forall l, t \tag{6}$$

$$\underline{y}_{gt} \le y_{gt} \le \bar{y}_{gt}, \quad \forall g, t \tag{7}$$

$$y_{gt}^r \le Y_{gt-1}, \quad \forall g, t \tag{8}$$

$$\underline{y}_{gt}^r \le y_{gt}^r \le \bar{y}_{gt}^r, \quad \forall g, t \tag{9}$$

$$Y_{gt} = Y_{g0} + \sum_{t'=1}^{t} y_{gt'} - y_{gt'}^r, \quad \forall g, t \tag{10}$$

$$\underline{Y}_{gt} \le Y_{gt} \le \bar{Y}_{gt}, \quad \forall g, t \tag{11}$$

$$\sum_g \sigma_g Y_{gt} \ge D_t PRM, \quad \forall t \tag{12}$$

$$\sum_{g\in G_b} p_{gtmh} + \sum_{l\in L_b^{In}} f_{ltmh} - \sum_{l\in L_b^{Out}} f_{ltmh} + u_{btmh} = d_{btmh}, \quad \forall b, t, m, h \in H_m \tag{13}$$

$$0 \le u_{btmh} \le d_{btmh}, \quad \forall b, t, m, h \in H_m \tag{14}$$

$$-X_{lt} \le f_{ltmh} \le X_{lt}, \quad \forall l, t, m, h \in H_m \tag{15}$$

$$\underline{p}_g Y_{gt} \le p_{gtmh} \le Y_{gt}, \quad \forall g, t, m, h \in H_m \tag{16}$$

$$p_{gtmh} \le \rho_{gtmh} Y_{gt}, \quad \forall t, m, g \in G^{RE}, h \in H_m \tag{17}$$

$$p_{gtmh} \le p_{gtm(h-1)} + \beta_g, \quad \forall g, t, m, h = 2, \dots, H_m \tag{18}$$

$$p_{gtmh} \ge p_{gtm(h-1)} - \beta_g, \quad \forall g, t, m, h = 2, \dots, H_m \tag{19}$$

$$p_{gtmh} = q_{gtmh}^- - q_{gtmh}^+, \quad g \in G^s, \forall t, m, h \in H_m \tag{20}$$

$$q_{gtmh}^+ \le \lambda Y_{gt}, \quad g \in G^s, \forall t, m, h \in H_m \tag{21}$$

$$q_{gtmh}^- \le \lambda Y_{gt}, \quad g \in G^s, \forall t, m, h \in H_m \tag{22}$$

$$Q_{gtm(h+1)} = Q_{gtmh} + \eta_g^+ q_{gtmh}^+ - q_{gtmh}^- / \eta_g^-, \quad g \in G^s, \forall t, m, h = 1, \dots, (H_m - 1) \tag{23}$$

$$0 \le Q_{gtmh} \le Y_{gt}, \quad g \in G^s, \forall t, m, h \in H_m \tag{24}$$

$$Q_{gtm1} = Q_{gtmH_m}, \qquad g \in G^s, \forall t, m \tag{25}$$

$$\sum_g \sum_m w_m \sum_{h \in H_m} e_g p_{gtmh} \le \bar{e}_t, \qquad \forall t \tag{26}$$

The transmission capacity available to install each stage is controlled with (4). The total existing transmission capacity is tracked with (5). Constraint (6) gives total capacity limits for each transmission corridor. Constraint (7) gives upper and lower limits on new generation capacity installed in each stage. Constraint (8) ensures only existing capacity can be retired, and (9) enforces any planned retirements and maximum retirement limits. Constraint (10) tracks the total existing capacity for each generator. Constraint (11) gives upper and lower limits for the total generator capacity allowed. A planning reserve margin is enforced with (12).

Operating constraints are given with (13)-(26). Power balance at each bus is controlled with (13). Constraint (14) limits unmet demand to the total demand at each bus. Line flow limits are given in (15). Generation from dispatchable generators is limited with (16), and for intermittent renewables with (17). Ramp up and ramp down limits are enforced for dispatchable generators with (18) and (19).

Storage production is composed of charging and discharging components (20). Storage charging and discharging limits are enforced with (21) and (22). Storage state of charge is tracked with (23). Constraint (24) ensures the maximum state of charge cannot exceed the installed capacity. Constraint (25) forces storage to begin and end a time slice at the same state of charge; this is a heuristic to balance charging and discharging. Annual carbon emissions are calculated and any policies limiting emissions are represented with (26).

High Impact Events and Hardening Investments

High-impact, low-probability events n can be modeled as a special class of time block m in the formulation above. That is, events can be treated as a subset of the model's representative time blocks, $n \in N \subset M$, and so all the constraints above can be applied to events. This section will introduce additional constraints and considerations needed to model disruptions during events, as well as the resilience options that might be used to mitigate those disruptions. The main components of modeling extreme events are hazards that disrupt asset operations or cause damages, hardening options that protect against hazards, and constraints to limit risk in events.

Sets and Indices

$n \in N$ Events

$z \in Z$ Hazards

$k \in K$ Hardening options

$k \in K_z$ Hardening options that protect against hazard z

Parameters

c_{lt}^{kx}, c_{gt}^{ky} Costs of hardening option k

c_{gtmh}^{kV} Variable operating costs of generators retrofitted with hardening option k

$\delta_{ztlnh}^{x}, \delta_{ztgnh}^{y}$ Derating factor due to hazard z during event

$\Delta_{ztlnh}^{x}, \Delta_{ztgnh}^{y}$ Damage risks from hazard z striking asset l or g during event

$\phi_{kz}^{x}, \phi_{kz}^{y}$ Derating protection provided by hardening option k against hazard z

$\phi_{kz}^{ax}, \phi_{kz}^{ay}$ Damages protection provided by hardening option k against hazard z

ψ_{kg} Capacity changes resulting from hardening retrofit

μ_t^u, μ_t^a Risk limits

Variables

x_{lt}^{k} Hardening investment in option k for transmission lines

x_{lt}^{kr} Retirement of hardening investment k

X_{lt}^{k} Existing hardened transmission capacity of type k

y_{gt}^{k} hardening investment k for generators

y_{gt}^{kr} Retirement of hardening investment k

Y_{gt}^{k} Existing hardened generation capacity of type k

p_{gtmh}^{k} Power output from hardened generator when hardening option k changes efficiency

$a_{zltnh}^{x}, a_{zgtnh}^{y}$ Damages realized from hazard z impacting an asset during event n

Since high-impact, low-probability events are low-probability, the event weight $w_n \approx 0$ and so event operating costs will not influence the objective function value. Instead, the events serve as conditions in which a given risk threshold must not be violated. This requires a new constraint, such as (27), in which unmet demand in the event set is constrained to fall below a threshold. While the events themselves may not influence the objective function, the investment alternatives that help to reduce event risk will still incur costs, so the model is seeking the least-cost expansion plan that limits event risk.

$$\sum_{h \in H_n} \sum_{b} u_{btnh} \leq \mu^u, \qquad \forall t, n \tag{27}$$

Asset derating or shutdown from hazard z can be modeled with constraints on generation or line flows. The severity of the impact is controlled with δ parameters; assets that are not exposed to a hazard in a particular event have $\delta = 0$, whereas when $\delta = 1$ the hazard completely takes the asset offline, values $0 < \delta < 1$ indicate partial deratings. Transmission lines that are derated by exposure to a hazard in an event can be modeled with (28), and for generators with (29). Note p-min constraints may need to be relaxed to maintain feasibility for impacted generators.

$$|f_{ltnh}| \leq (1 - \delta^x_{zltnh})X_{lt}, \qquad \forall z, l, t, n, h \in H_n \tag{28}$$

$$p_{gtnh} \leq \left(1 - \delta^y_{zgtnh}\right)Y_{gt}, \qquad \forall z, g, t, n, h \in H_n \tag{29}$$

If hardening options exist that protect against hazard z, then the constraints become (30) for transmission and (31) for generation. The protection factor $0 \leq \phi_{kz} \leq 1$ can be used to model partial protection provided from hardening option k. The generation constraint is appropriate for renewable generators if the desired behavior is for the generator output to be limited to the lesser of the renewable capacity factor and the derating factor. If instead the derating factor should downscale the renewable output, then the impacted generator constraint becomes (32).

$$|f_{ltnh}| \leq (1 - \delta^x_{zltnh})X_{lt} + \delta^x_{zltnh} \sum_{k \in K_z} \phi^x_{kz} X^k_{lt}, \qquad \forall z, l, t, n, h \in H_n \tag{30}$$

$$p_{gtnh} \leq \left(1 - \delta^y_{zgtnh}\right)Y_{gt} + \delta^y_{zgtnh} \sum_{k \in K_z} \phi^y_{kz} Y^k_{gt}, \qquad \forall z, g, t, n, h \in H_n \tag{31}$$

$$p_{gtnh} \leq \rho_{gtnh} \left[\left(1 - \delta^{y}_{zgtnh}\right) Y_{gt} + \delta^{y}_{zgtnh} \sum_{k \in K_z} \phi^{y}_{kz} Y^{k}_{gt} \right] \quad g \in G^{RE}, \forall z, t, n, h \in H_n \tag{32}$$

In addition to disrupting operations, hazards that strike insufficiently protected assets can cause damages. The damages may be to the asset itself, the surrounding community, or the environment. If these damages are unacceptable, constraint (33) for transmission and (34) for generation will force either the hardening or retirement of existing assets and will prevent unhardened investments in new assets. However, if some damages are allowed, the alternative constraints (35) and (36) can be used. Then, events that impact an exposed asset will result in damages a. The severity of the damages is determined by Δ and any partial protection ϕ^{a}_{kz} from hardening.

$$\sum_{k \in K_z} X^{k}_{lt} \geq X_{lt}, \quad \forall\, l, t \tag{33}$$

$$\sum_{k \in K_z} Y^{k}_{gt} \geq Y_{gt}, \quad \forall\, g, t \tag{34}$$

$$a^{x}_{zltnh} \geq \Delta^{x}_{zltnh} \left(X_{lt} - \sum_{k \in K_z} \phi^{ax}_{kz} X^{k}_{lt} \right), \quad \forall z, l, t, n, h \in H_n \tag{35}$$

$$a^{y}_{zgtnh} \geq \Delta^{y}_{zgtnh} \left(Y_{gt} - \sum_{k \in K_z} \phi^{ay}_{kz} Y^{k}_{gt} \right), \quad \forall z, g, t, n, h \in H_n \tag{36}$$

These damages can be given a cost and added to objective function, but since the probability of the event is likely unknown, it will often be preferable to constrain the total damage risk to a threshold as (37). Damage costs can be combined with the costs of unmet demand to form a composite risk limit (38).

$$\textstyle\sum_z \sum_g \sum_{h \in H_n} \left(a^{y}_{zgtnh} + a^{x}_{zltnh} \right) < \mu^{a}, \quad \forall t, n \tag{37}$$

$$\sum_z \sum_g \sum_{h\_H_n} \left(a^y_{zgtnh} + a^x_{zltnh}\right) + \sum_b \sum_{h \in H_n} c^u u_{btnh} \leq \mu, \qquad \forall t, n \tag{38}$$

The total investment in hardening is controlled in the same way as normal investments. Transmission hardening is shown in (39) and generation hardening in (40). It will usually be desirable to limit the sum of hardened assets to the total installed capacity of the asset to prevent extra hardening that provides an unrealistic level of protection as in (41) and (42). If two or more hardening options can be installed together to provide additional protection, such a configuration is best modeled as its own option k with their associated investment variables.

$$X^k_{lt} = X^k_{l0} + \sum_{t'=1}^{t} \left(x^k_{lt'} - x^{kr}_{lt'}\right), \qquad \forall k, l, t \tag{39}$$

$$Y^k_{gt} = Y^k_{g0} + \sum_{t'=1}^{t} \left(y^k_{gt'} - y^{kr}_{gt'}\right), \qquad \forall k, g, t \tag{40}$$

$$\sum_{k \in K_z} X^k_{lt} \leq X_{lt}, \qquad \forall l, t \tag{41}$$

$$\sum_{k \in K_z} Y^k_{gt} \leq Y_{gt}, \qquad \forall g, t \tag{42}$$

Hardening may have performance implications in normal operating conditions, such as reduced capacity or efficiency reductions. Asset capacity reduction by a factor ψ_{kg} of can be modeled with (43). Hardening retrofits that change the efficiency of a generator can be modeled with the introduction of a new operation variable that represents production at the new cost and with constraint (44), which activates the new variable, and constraint (45) which eliminates the old production variable. In this situation, similar constraints around ramping or retirement plans will also need to be enforced for the new variables. It is important to note here that the time block subscript is m because the production during normal operating conditions is affected.

$$p_{gtmh} \leq Y_{gt} - \psi_{kg} Y^k_{gt}, \qquad \forall g, t, m, h \in H_m \tag{43}$$

$$p_{gtmh} \leq Y_{gt} - Y^k_{gt}, \qquad \forall g, t, m, h \in H_m \tag{44}$$

$$p^k_{gtmh} \leq Y^k_{gt}, \qquad \forall g, t, m, h \in H_m \tag{45}$$

The new objective function resulting from this formulation will include new terms for the hardening investment costs and any performance changes resulting from the retrofits. The investment component becomes (46), the operation component becomes (47), and the final discounted objective function is (48).

$$INV'_t = \sum_l \left(c^x_{lt} x_{lt} + c^{kx}_{lt} x^k_{lt}\right) + \sum_g \left(c^y_{gt} y_{gt} + c^F_g Y_{gt} + c^{ky}_{gt} y^k_{gt}\right) \tag{46}$$

$$OPS'_t = \sum_m w_m \sum_{h \in H_m} \sum_g \left(c^V_{gtmh} p_{gtmh} + c^{kV}_{gtmh} p^k_{gtmh}\right) + \sum_b c^u u_{btmh} \tag{47}$$

$$\min \sum_{t \in T} \gamma_t [INV_t' + OPS_t'] \tag{48}$$

These constraints and variables provide all principles required for modeling extreme events in most resilience planning models. Modelers with requirements that are not covered here will benefit more by shaping the formulation to the intractable details of their specific problem.

Event Risk Profiles and Limits

The risk limit constraints are a central component of the formulation, so the ability to structure these constraints to accomplish specific aim will be valuable to planners. This can be done by adding nuance to the VoLL to better reflect the costs of disruptions and by changing the risk limit constraints to give planners more control over the shape of the overall risk profile.

Dynamic Value of Lost Load

The cost applied to unmet demand, the value of lost load (VOLL), is most simply modeled as a constant. But in practice, lost load can be more consequential in some cases, and for some customers, than in others. The true value of lost load depends on several factors including the affected customers and the duration of the disruption. For example, during extreme conditions, the customers exposed to hazards may be especially vulnerable to harm, so maintaining service to these customers may reasonably be prioritized. Dynamic VoLL penalties allow for more nuanced representation of these consequences.

One form of dynamic VoLL uses indexes by location and time of occurrence to increase the penalties associated with disruptions to vulnerable customers c^u_{btnh}. One drawback of this approach is the data requirements. The method requires as inputs VoLL for each location and hour during events. This requires analysis that may be costly to conduct, and the values must be considered carefully to ensure that customers receive equitable treatment.

Unserved energy can also be broken into hierarchical groups with increasing penalties. Then, disruptions of an especially large magnitude or duration at a given location will be discouraged relative to minor and dispersed service interruptions. For groups $j = 1, \dots, J$ with increasing costs $c^u_1 \le c^u_2 \le \cdots \le c^u_J$, the demand balance constraint becomes (49), the allowance of each group can be limited to $\bar{u}_j$ with (50), and the total VoLL is calculated and limited with (51).

$$\sum_{g \in G_b} p_{gtnh} + \sum_{l \in L_b^{In}} f_{ltnh} - \sum_{l \in L_b^{Out}} f_{ltnh} + \sum_j u_{btnhj} = d_{btnh}, \quad \forall b, t, n, h \in H_n \tag{49}$$

$$\sum_{h \in H_n} u_{btnhj} \le \bar{u}_j, \quad \forall b, t, n, j \tag{50}$$

$$\sum_{h \in H_n} \sum_b \sum_j c^u_j u_{btnhj} \le \mu, \quad \forall t, n \tag{51}$$

Finally, as noted in the high-impact event formulation section, unserved energy and other damages can be combined into a composite metric that better captures the total cost of leaving infrastructure vulnerable to hazards (52). This allows for many types of damages to be balanced and limited. This constraint is compatible with dynamic VoLL.

$$\sum_{h\in H_n}\sum_z\sum_g\left(a^y_{zgtnh}+a^x_{zltnh}\right)+\sum_{h\in H_n}\sum_b\sum_j c^u_j u_{btnhj}\le\mu,\qquad\forall t,n \tag{52}$$

Uniform Risk Limits

The risk constraints presented so far have applied a uniform threshold to every event. This uniform limit approach simple to implement. The simplicity of uniform limits also allows for more sophisticated approaches are modeled elsewhere. For example, if events are sampled from a larger event set, uniform limits work just the same without any changes.

It is also attractive because the standards of resilience are consistent across events; no events are held to a lower standard of service, so the method avoids questions around customer equity that could arise if some events are allowed more load shed than others.

Still, in some circumstances uniform limits may not be best. There may be threats in the event set that are difficult to address with capacity planning options; these threats may be more cost-effective to address with non-capacity options. In this case, a uniform risk limit may be difficult to apply because these ill-posed events may push the solution to unrealistic plans or even lead to an infeasible model.

Conditional Value at Risk Limits

Rather than uniformly limit the losses in each event, conditional value at risk (CVaR) allows planners to limit the expected losses in a percentile of the worst events α; the percentile being set by the user. The CVaR constraints are given in (53), where α is the user specified percentile of worst events, γ_t is a variable that settles to the value at risk quantity at the α percentile, and v_{tn} is a variable that tracks the unmet demand over VaR in each event. The variables γ_t and v_{tn} are constrained with (54) and (55).

$$\gamma_t+\frac{1}{\alpha|N|}\sum_{n\in N}v_{tn}\le\mu,\qquad\forall t \tag{53}$$

$$v_{tn}\ge\sum_{h\in H_n}\sum_b u_{btnh}-\gamma_t,\qquad\forall t,n \tag{54}$$

$$v_{tn}, \gamma_t \geq 0, \quad \forall t, n \tag{55}$$

For a given target value μ, CVaR is a relaxation of the uniform risk limits discussed above. This occurs because CVaR is given the flexibility to allocate extra unmet demand to some events while reducing it in others when it is cost-effective to do so. The result is that a CVaR risk limit will return plans with a lower total cost than uniform limits, the tradeoff being that the worst events will have more unmet demand.

The behavior of CVaR, accepting more load shed in some events, will be undesirable to some planners. But this behavior may be desirable when some threats could be more economically addressed with resilience options that are not included in the capacity expansion model. CVaR will automatically determine which threats are best met with capacity planning tools and which should be addressed in another way.

Planners are not limited to one or the other; both CVaR and uniform limits can be applied in the same model. In this case, the CVaR target must fall below the uniform target to be binding. Combining the two limit methods allows planners to further tailor the model's risk preferences.

Sampling Important Events

The number of events that can be included in a planning model is limited by computational power, so it is necessary to select a small subset of important events. An ideal event sample would be as small as possible while still producing the same optimal solution as a larger event set. Making such a selection, however, can be difficult because the events that lead to a particular solution are not obvious in advance.

We will use the notation $\tilde{n} \in \widetilde{N} \subset N$ to refer to a sampled subset of events and $\widetilde{N}^*$ to refer to a robust sample, which leads to the same solution as the event set N.

We will divide event selection methods into three categories: attribute-based methods, simulation-based methods, and iterative optimization selection methods. Attribute-based methods only use information from the events and model to deduce the important events without the use of any simulation or optimization runs. Simulation-based methods first simulate one or more candidate plans in a larger set of extreme events and then use performance metrics from the simulations to select important events. Iterative methods solve a series of optimizations in which the most deficient event or events from the previous iteration are added to the sample set for the next iteration; the cycle is repeated until the desired performance level is met in all events.

Attribute Based Selection

Attribute-based methods rely on information from the events to deduce which events are important in advance of any simulation or optimization runs. For example, such a method may choose events with high and low combinations of demand and wind speed. This approach lets planners select events based on criteria that are known to be important or conduct a sensitivity analysis on a particular metric. However, developing a successful attribute-based selection procedure faces two broad design challenges: getting the right data, and then selecting events from the data.

Building the dataset for an attribute-based selection method requires design choices over which attributes to use; whether the data should be scaled, preprocessed, or aggregated in any way; and how to handle attributes that apply to candidate investments versus existing infrastructure. For example, if wind power is an attribute of interest, the designer will face a question of whether to use windspeed as an attribute directly or convert it into wind power output from a generator. If one wind facility has a much higher capacity than a nearby facility, should the data be scaled to normalize the power output, or should the raw power magnitude be left in the data? If the absolute magnitude is important, how should candidate generators, which have a range of possible sizing options, be treated?

The answers to these questions depend on the aim of the particular study and the details of the system, but some principles serve as useful guides.

1) Choose attributes to be close to the actual optimization parameters. Rather than using heat and humidity as attributes, preprocess the data and convert it to the generator derating factor that will eventually feed into the optimization.
2) Omit needless attributes. Including too many attributes makes it harder for the selection process to identify the important features or combinations of features. This is not to say that modelers must avoid any nuance, but that every attribute should be selected judiciously.
3) Scale attributes only when necessary. Dissimilar attributes, and those with different units, will often need to be scaled to prevent the larger values from dominating the smaller. But scaling alike attributes removes information from the data and is more likely to obscure, rather than highlight, the important parameters.

An attribute-based aggregation that is relevant for resilience planning is capacity at risk. Capacity-at-risk quantifies the total capacity that is unavailable during an event. The metric aggregates deratings, forced shutdowns, and poor renewable resource availability throughout the system to arrive at a total value. Excess load beyond what would normally be observed can also be included. While capacity at risk follows the principles for good attributes given above, there are still some ambiguities. For one, the hazard that causes outages is relevant for resilience planning, so it might be useful to categorize the outages by cause. Also, quantifying line capacity at risk is sensitive to how lines are defined. A series of short line segments may have a much larger apparent capacity than if they were aggregated into a single long branch.

The second design complexity for this class of method is in devising the actual procedure for selecting events. Intuitively, a good event set will cover the most severe events as well as all the different underlying issues that could ultimately cause disruptions. Without simulating the events, however, it is not clear which extremes are stressful and which variations are different enough to cause a new sort of failure. We will examine five selection methods with different approaches to this challenge.

Maximum Capacity at Risk

This metric calculates the capacity at risk from each event and then selects the $|\widetilde{N}|$ events with the largest total values. This approach is simple, and it ensures that several variations of the most disruptive conditions will be included in the sample.

But this approach is likely to favor one type of hazard while ignoring others to which the system is vulnerable. For example, this approach might exclusively select summer heatwave events while ignoring extreme winter chill events. The resulting model may protect against heatwaves while leaving the system vulnerable to disruption from cold. The same type of problem can favor samples that disproportionally represent a particular asset class or region of the system. Hazards that cover dense sections of short, high-capacity transmission might dominate the selection.

Categorized Capacity at Risk

More diverse samples can be found by categorizing the capacity at risk by hazard and asset class. For example, one category might be transmission assets shut down by wildfire risk and another category would be generation deratings due to high heat. For J categories, the $\left|\widetilde{N}\right|/J$ events with the largest capacity at risk from each category can be collected into the final sample.

Clustered Selection

Clustered selection methods use an automatic clustering method, such as k-means, to form groups of similar events and then select an event from each cluster according to some criteria. Often the most average point, often termed the medoid, from each cluster is chosen. But it may be preferable to select the most severe event from each cluster instead of the most typical point.

A clustered approach is an automatic way to identify categories for the events. A clustered approach would be preferable over user-defined categories when there are groups of hazards that commonly occur together to create dynamics that are difficult to delineate with user defined categories. Clustering may also be attractive because the method is automatic; it provides systematic criteria to justify the event selection beyond subjective user-defined preferences.

D-Optimality

D-Optimality is a method from the design of experiments subfield of statistics. A D-Optimal design is the collection of points that maximizes the determinant of the design matrix, as in (56). Where for P attributes, $\boldsymbol{X}$ is the $|\widetilde{N}| \times P$ matrix of sampled event attributes. The method was originally developed to select points near the extreme limits of the design space to reduce the variance in regression parameter estimates. While the optimization function in (56) is technically NP-Hard, the determinant can be updated quickly as points are added or removed from the sample $\widetilde{N}$ so efficient search procedures exist to find near optimal designs.

$$\max_{\tilde{n}} \det(\boldsymbol{X}^\top \boldsymbol{X}) \tag{56}$$

S-Optimality

S-Optimality is an alternative to D-optimality. S-optimal designs try to select points that are far away from one another by maximize the harmonic mean distance between each selected event and its nearest selected neighbor. D- and S- optimal designs are usually similar, but D-optimal design may try to repeat events at larger sample sizes. S-optimal designs will not repeat events, but S-optimal selection algorithms are much slower to compute at large sample sizes due to the lack of efficient updating procedures.

Performance-Based Selection

Performance-based methods simulate one or more candidate plans in the set of extreme events and then use performance metrics from the simulations to select disruptive events. The performance metrics address one vexing issue with attribute-based methods: identifying which events are disruptive. But performance-based selection methods still face the same design challenges as attribute-based methods, namely which metrics to use and how to select events from the resulting data. Performance-based methods also face the question of how to select the initial expansion plans to simulate.

The best performance metrics for guiding an event sample are often the same metrics that are targeted in the capacity planning model. If the optimization's risk control constraints limit unmet demand in events or a composite metric of damages and the total value of lost load, then the same metrics in simulated events will be relevant.

The initial expansion plans that will be simulated do not have to be near-optimal plans. In fact, it is better if the plans are deficient because it helps to identify the events and conditions that will cause problems if ignored by the optimization. The method to generate candidate plans, then, does not need to be advanced. Simple planning heuristics, simplified optimizations representing a small number of randomly chosen events, and even the random selection of investments are all viable methods for arriving at a collection of initial plans.

Maximally Disruptive Events

This approach selects the events with the largest disruptions as measured by the relevant simulation performance metric. This ensures that all of the most disruptive events are included. But like capacity at risk, the method can still struggle to avoid redundant events that represent the same underlying failure mechanism.

ALFA

This approach from the academic literature selects operating conditions for transmission and generation planning models. Rather than selecting the most disruptive events, this method selects events based on the variance and covariance of the performance metric across the simulations with different candidate plans. Correlations from the simulations of different plans are used to identify and avoid redundant events that represent the same failure mechanism and are thus fixed by the same investments. This method is especially powerful because it first selects the most disruptive events, but then at larger sample sizes, it favors events that represent unique types of disruptions, even if the absolute magnitude of the disruption is small compared to the worst events.

Iterative Optimization and Event Selection

Iterative methods work in a loop where first an expansion model is solved, then the resulting plan is simulated in more detail, and finally the most deficient event or events are selected and included in the sample for the next iteration. This guarantees that each selected event is both important (because the event causes a disruption) and non-redundant (because selections without the event resulted in deficiencies). While this approach will not necessarily find the smallest possible robust sample, it will generally be more successful at finding small, robust samples than other approaches.

Of course, an iterative approach is computationally costly because it requires a series of capacity expansion optimizations and a series of event simulations, each of which are among the two most computationally expensive steps of the planning process. A single run of these two programs can take hours of processor time, and if dozens of events are needed, a simple iterative approach will be unrealistic on its own.

Techniques to reduce the iteration count are especially valuable here. One possibility is to start the first iteration with an already strong selection of events from a different sampling method; then only the few outlier events need to be identified and added to the sample. Another way to reduce the iteration count is to select more events per iteration; this will result in some redundancy in the sample but ultimately running fewer iterations will outweigh the computational cost of slightly larger optimization models.

The computational cost of the optimization and simulation steps can also be reduced. The optimization run time can be reduced by using the solution from the previous iteration as a starting point in the next run. The simulation step can be expedited by only simulating events that were deficient in the previous iteration; the full event set will then only be simulated as a final check once a robust plan has seemingly been found.

Test System

System Data

We demonstrate these resilience planning principles on a small network with 6 buses, 9 line corridors, and 26 generators. All system components are assigned coordinates, which are used to determine whether the component is exposed to hazards. The system and asset coordinates are shown in Figure 1 and is loosely based on the Garver test system [43]. Four investment stages are modeled with progressively worsening climate parameter ω, which determines the severity of hazards in events. The model was developed and run using the adaptive coordinated expansion planning tool (ACEP) [44]

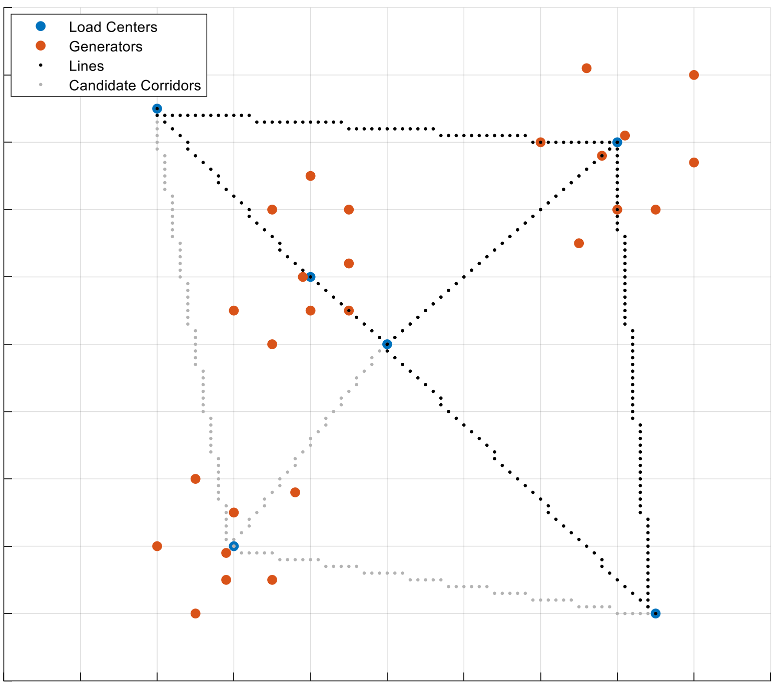

Figure 3: Test system schematic and asset coordinates

Hazards and Events

Hazards representing extreme heat and wildfires are represented in this system. We use an event creation algorithm to construct hazardous events based on the climate parameter and several random variables. In practice, planners might use historical weather data or weather simulations might to construct and event set.

Extreme heat causes generation and transmission deratings as well as demand increases. The magnitude of the derating depends on the system component and the temperature of the heat event. The size, location, and temperature of heat hazards are all functions of random variables and the climate scenario parameter.

We break wildfire hazards into two categories: fire ignition risk conditions, in which grid operations are at risk of igniting a fire; and active wildfire conditions, in which a wildfire is ongoing near system components. Ignition risk conditions can force preventative shutdowns of equipment, whereas active fire conditions require generator crew evacuations and equipment shutdowns. We use the shorthand Level 1 (L1) to refer to ignition risk fires and Level 2 (L2) to refer to active fire conditions.

The quantity, location, and severity level of wildfire hazards in each event are functions of random variables and the climate scenario parameter.

Wildfire hazard movement is modeled according to a vector field representing the wind patterns of the region. The vector field points counterclockwise around the map, and its magnitude is weakest near the center of the map and strongest around the periphery, especially in the northeast and southwest regions.

Hardening Options

Two hardening options are available for transmission and one for generation. The first option, available to both transmission and generation, represents overhead covered conductor transmission lines and other equipment that reduces the risk of igniting a wildfire. Assets hardened with this option can operate as normal under fire ignition risk conditions, but still cannot operate under active wildfire conditions due to assumed damage to the asset.

The second option, available only to transmission, represents underground transmission lines. This option is significantly more expensive, but it protects the transmission line during active wildfire conditions. We assume this option allows for normal transmission operations under all fire hazards because the ground acts as a heat barrier for the equipment [15]. We do not model a similar option for generators because generator crews are assumed to be evacuated during active wildfire conditions, so no hardening option is available that would allow generators to continue normal operations during an active wildfire.

Results and Analysis

Case Study Solutions

In this section we briefly summarize the results of the planning study. These results are specific to this case study and its assumptions, and as such should not be taken to be representative of other systems or resilience planning in general. The results are primarily intended to demonstrate the methods discussed in this report.

Comparison of Baseline and Resilient Solutions

We run the planning optimization with event risk limits ranging from the baseline plan, which allows unlimited unmet demand in events, to a fully robust plan, which does not allow any unmet demand in any event. This allows us to compare the baseline plan to the fully robust plan and to track the transition from one to the other. Doing so allows us to observe some of the possible outcomes of resilience planning, as well as some of the insights that might emerge from resilience plans in real systems.

We find that, relative to the baseline plan, the resilient plan builds more transmission capacity, and it builds the transmission in earlier stages, Figure 2. This implies that transmission redundancy is a key source of resilience for this model. The additional transmission allows for increased power transfers between nodes even when some lines are inoperable.

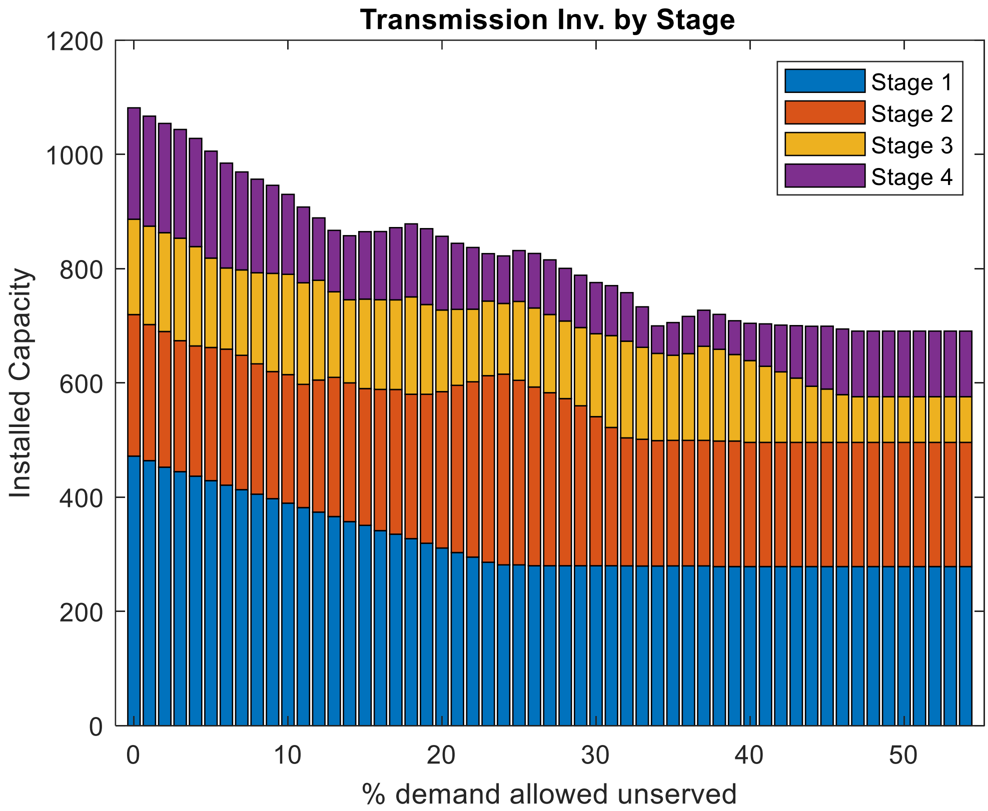

Figure 4: Transmission investments increase and are made earlier in resilient plans

The resilient plan also invests heavily in both transmission hardening options, and much of these hardening investments occur in the early stages of the model Figure 3 and Figure 4. Line undergrounding is preferred in the more resilient plans despite its much higher costs. The early investment in hardening for these assets indicates that, while more drastic hardening measures may not be immediately necessary, it may be beneficial to preemptively take stronger measures if they are likely to be necessary in the long-term future. Because many utilities attempt to gradually phase climate resilient investments in to the normal asset replacement and maintenance cycle, this result indicates that such a strategy may be possible, but must begin early.

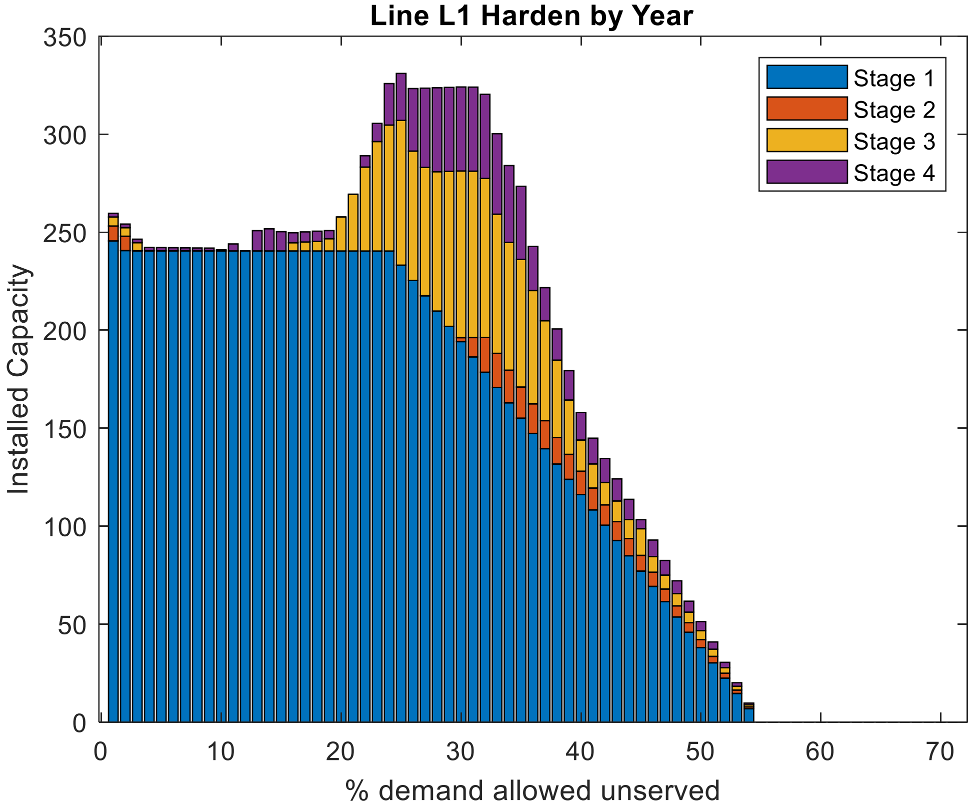

Figure 5: Covered conductor line hardening

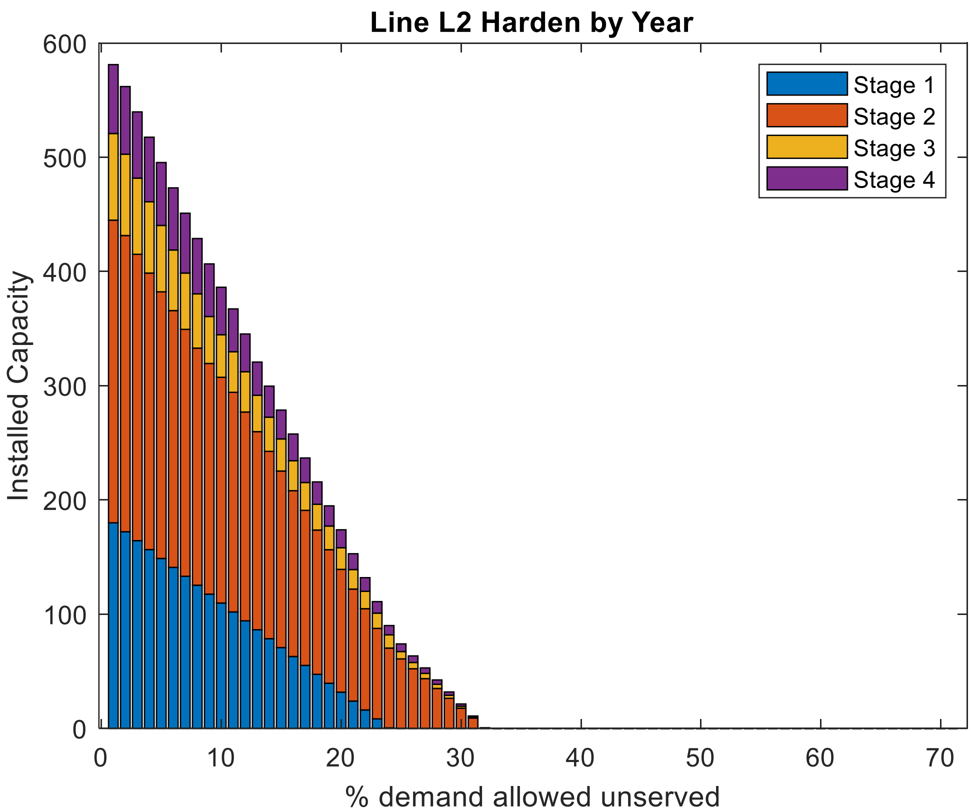

Figure 6: Line undergrounding

Conversely, the resilient plan does not change the timing or magnitude of generation investments. The only change in the generation expansion plan is relocating one CCGT from the highly exposed location at bus 1, to the unexposed location at bus 6. This new location has a higher natural gas fuel price and requires new transmission to connect to the rest of the network, which is why the baseline plan rejects that candidate project. But the frequent disruptions at bus 1, and the additional transmission capacity in the system overall, ultimately make the location at bus 6 more attractive despite the higher fuel cost.

While the resilient plan does not install more generation capacity, generator plans for retirement are delayed in the resilient plan. Instead, the generators are kept online for use as emergency capacity during extreme events.

Some generators are hardened against fire risk in the resilient plan, but the overall investment in generation hardening is well below transmission hardening Figure 5. This is not especially surprising because we are assuming that generators will need to evacuate their operations crews during fire events for occupational safety. This means there is no hardening option that allows generators to stay online during wildfires, whereas such an option does exist for transmission. Given these assumptions, the preferred strategy is to locate generation in a safe, remote region and invest in fully hardened lines running into high-risk regions. This strategy provides consistent resilience and is worth the higher cost of fully hardened lines.

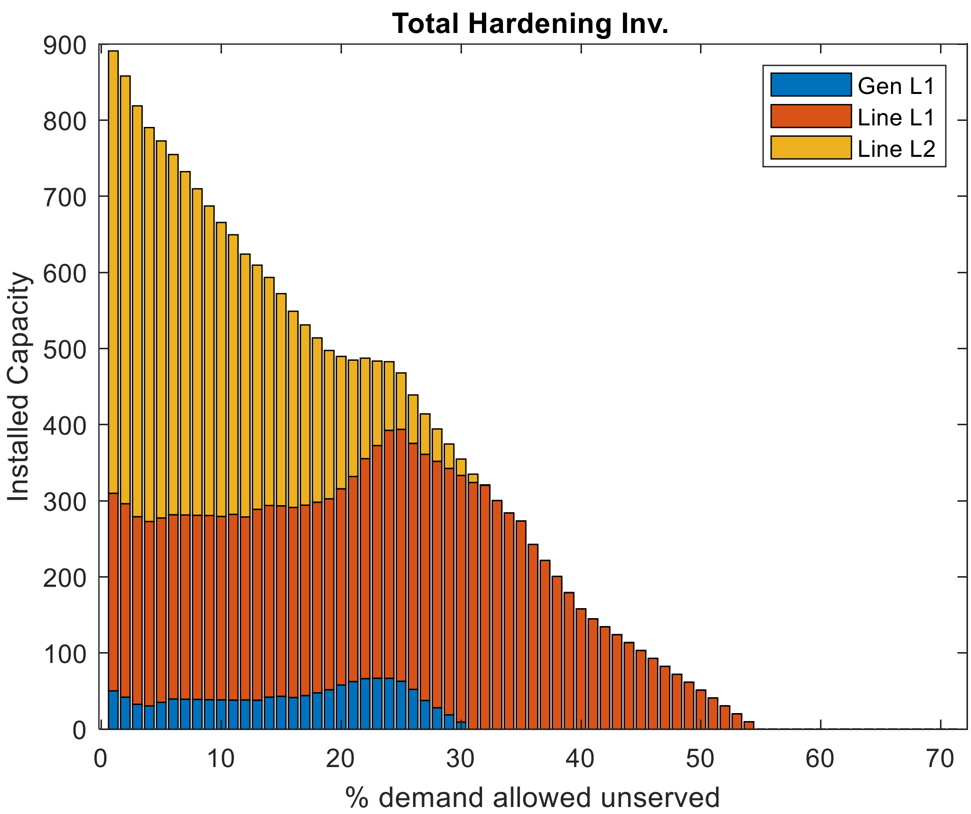

Figure 7: Most hardening investments are for transmission

While the net investment in transmission increases in the resilient plan, the transmission corridors that receive upgrades differ substantially between the baseline and resilient plans. Several corridors that are upgraded in the baseline plan or a partially resilient plan are avoided in the resilient plan, in favor of corridors that are not upgraded in the baseline plan. In Figure 6 corridors 1 and 7 are upgraded in the baseline plan but not the resilient plan; corridors 4 and 6 are upgraded in the resilient plan but not the baseline plan. Corridor 2 is only upgraded in some intermediate levels of resilience, indicating several strategies are possible to provide different levels of resilience. This indicates that ignoring resilience in plans today may result in both maladaptive investments that would be avoided with better planning frameworks and in missed investments that provide resilience that is not valued appropriately with current capacity planning tools.

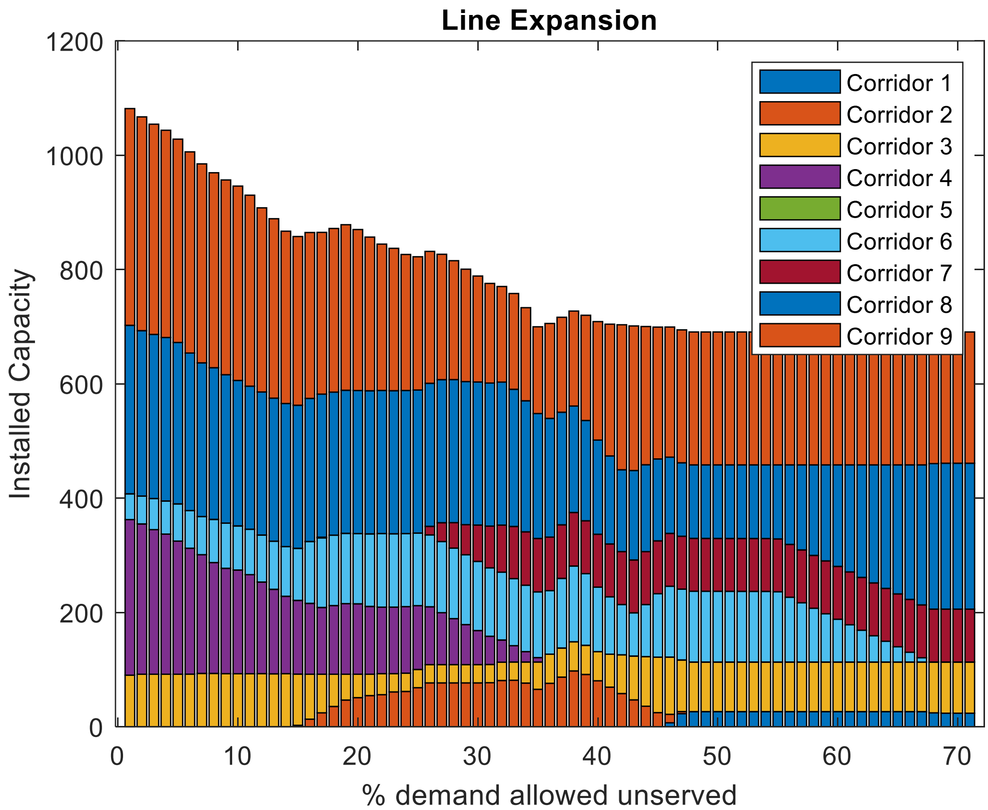

Figure 8: Resilient plans select different corridors for capacity expansion

While the total cost from the resilient plan's objective function increases due to the additional investments and hardening, we find that the cost increase is accompanied, and partially offset by, reduced operating costs on average Figure 7. This results from the more robust transmission network allowing for higher penetration of lower cost generation and renewables. It is also worth noting that while the objective function cost of the resilient plan increases relative to baseline, this does not indicate that the true cost of the resilient plan is greater because the vulnerability of the baseline plan to extreme events is substantial. Some of the considered events would result in catastrophic disruptions and damages under the baseline plan.

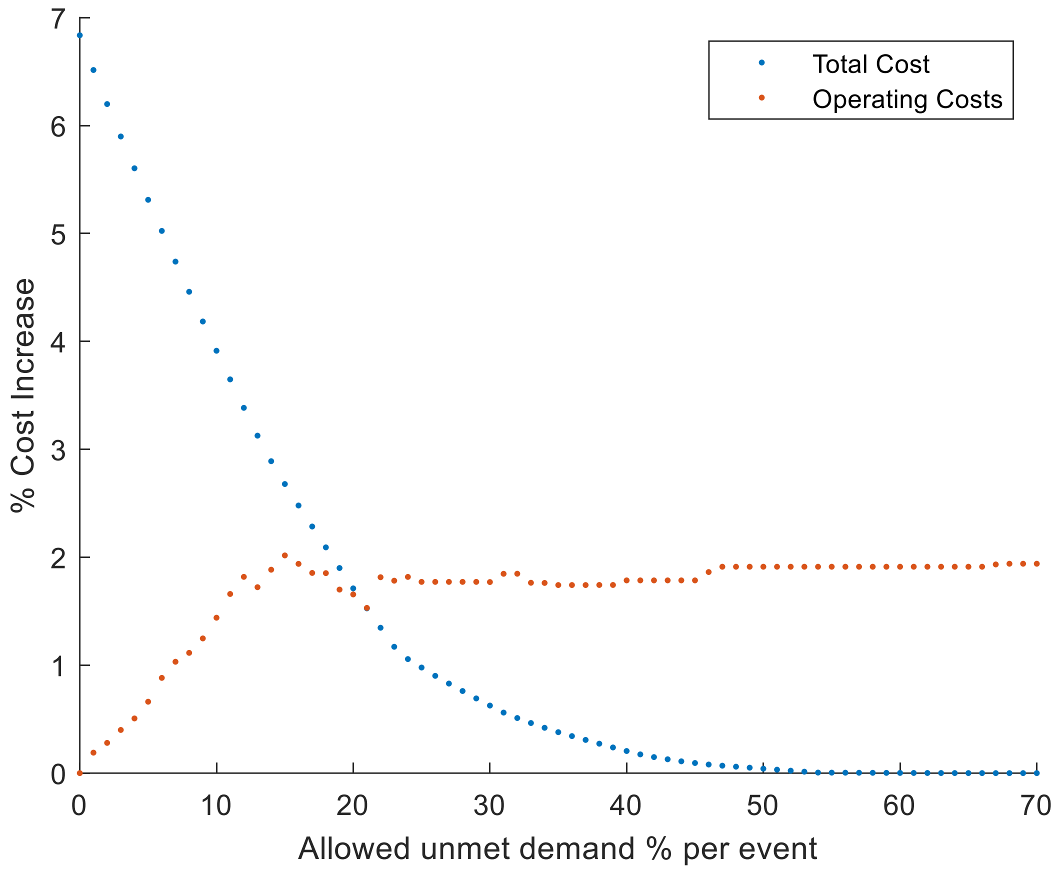

Figure 9: Resilient plans total cost increase while operating costs fall

Risk Profile Constraints

We compare uniform risk limits to the CVaR limit constrains. Recall that CVaR constraints are a relaxation of uniform limits, so the CVaR solutions will have a lower cost for a given target while allowing greater unmet demand in the worst events. Figure 8 shows that this cost difference between the two profile methods is small in percentage terms, generally never more than 0.25%. Conversely, Figure 9 shows the worst unmet demand event for CVaR can increase by about 10%.

This tradeoff might appear unattractive at face value, but the comparison of the two risk profiling constraints is valuable for evaluating possible options that were not considered in the capacity expansion planning model. For example, dozens of operations changes might be available to mitigate the worst events at a lower cost than the 0.25% difference between candidate plans, but these operational practices are not represented in the expansion model.

The different risk profiling methods are helpful for estimating the marginal value of protection in the worst events.

Often fixed investments are not the most cost-effective means to address vulnerabilities so the CVaR method helps to automatically avoid the most expensive investments that are only needed for a few events.

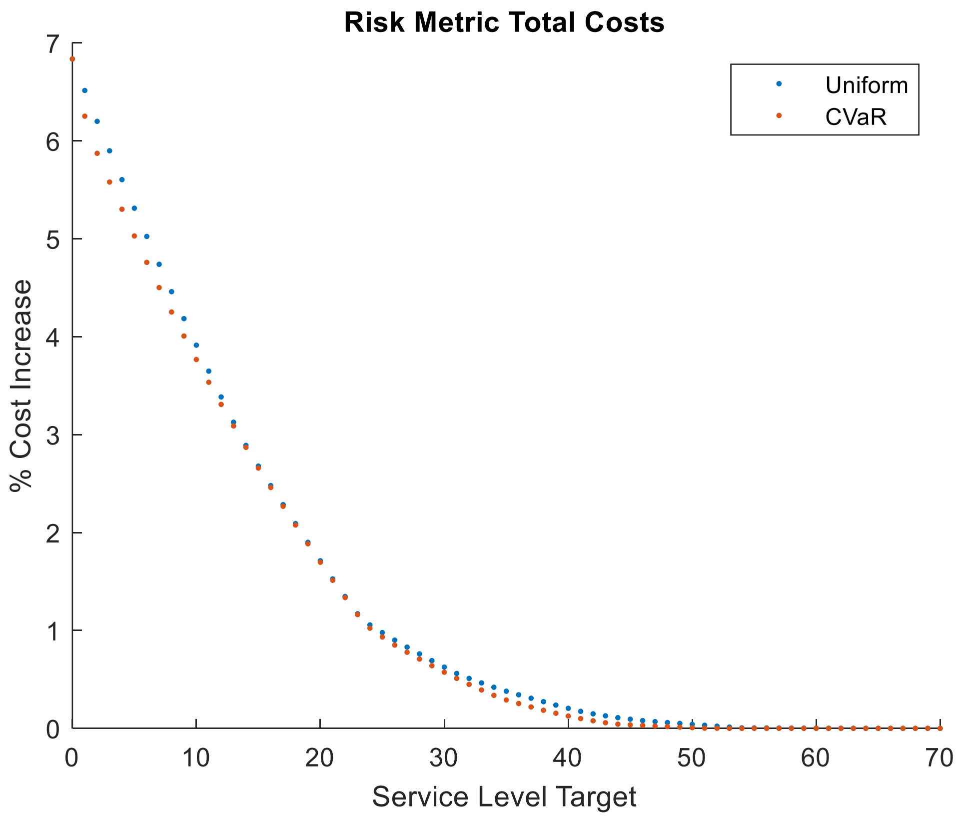

Figure 10: Risk limit profile costs per threshold.

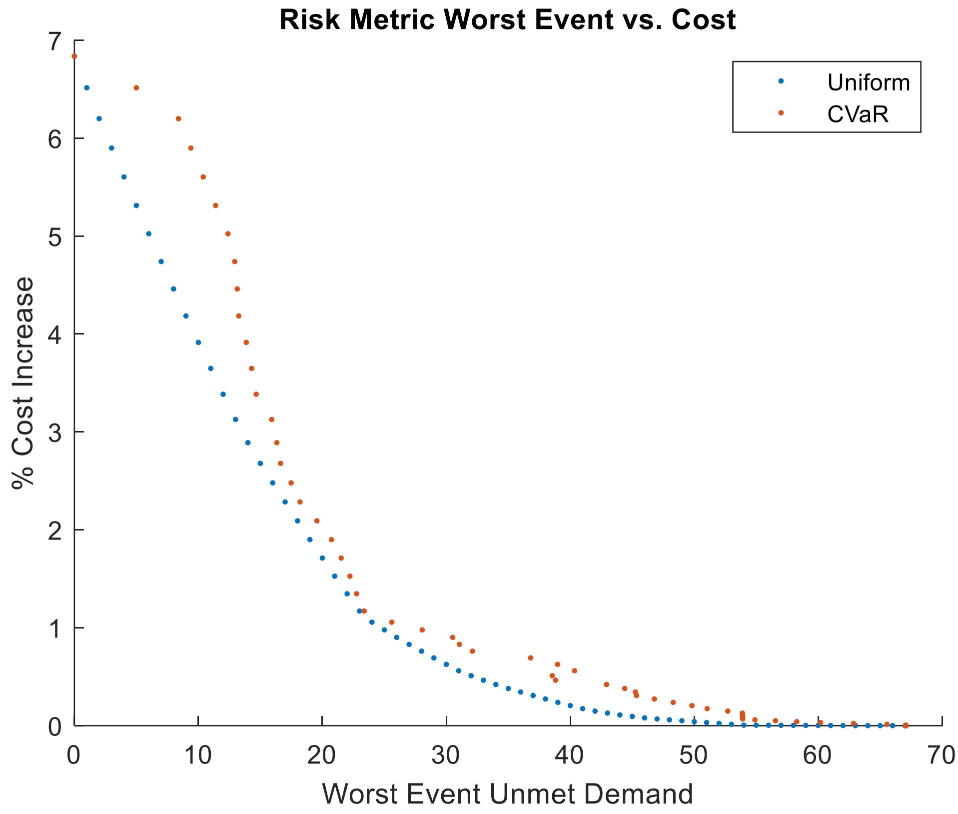

Figure 11: Risk profile worst event versus cost

Sampling Events

We test the event selection methods with sample sizes ranging from 1 to 50 events. The unmet demand allowance is set to zero for the sampled events, so each model is attempting to find the fully robust plan. Once the optimal solution is found for a given method and sample size, the solution is simulated on the full set of constructed events and the total unmet demand over the event set is calculated. Figure 10 compares some of the methods against random sampling as a benchmark. Figure 11 compares the iterative method, max capacity at risk to the two simulation-based methods: max unmet demand, and ALFA. Figure 12 shows the same data as 10 but with a y-axis limit to show only near optimal results.

At small sample sizes, the iterative method has the worst performance of the tested methods; it quickly improves, but only at sample sizes over ten does the iterative method outperform the other high performing methods. However, with only 16 sampled events, the iterative method successfully finds the optimal robust expansion plan. Only one other selection method (ALFA) finds the robust plan, and 30 sampled events are needed for ALFA to do so. So, perhaps unsurprisingly, the iterative optimization and selection approach is the best-in-class method for finding a robust selection of events. Since the method does not outperform other methods at small sample sizes, it may be possible to improve the method by starting with a sample from one of the other approaches.

As noted, the only other method that finds the robust expansion plan is ALFA, which does so fairly consistently with sample sizes of at least 30. ALFA is also has some of the best performance at smaller sample sizes. As a simulation-aided performance-based method, ALFA requires simulations of candidate plans to make its selection. These simulations can be done in parallel and do not require expensive optimizations to find the plans as the iterative method does, so ALFA represents a computational savings over the iterative method as long as the larger event sample is still tractable in the optimization.

Maximum capacity at risk is one of the strongest selection methods for this case study. At many of the smaller sample sizes, this method returns the best plans. While the method never identifies the robust expansion plan, the out-of-sample unmet demand is substantially reduced. Maximum capacity at risk also requires the least computation of any of the tested methods; it relies entirely on the sorted asset derating information that is given to the optimization model. However, while the method has strong performance in this case study, this is at least partially an artifact of the details of the system. A larger system with more hazards and hardening options would present more diverse events, which would deteriorate the performance of this approach.

Categorized capacity at risk does not, for the most part, improve on the performance of the maximum capacity at risk method. But the method does have strong performance, and it should protect against some of the scaling risks faced by maximum capacity at risk. Likewise, the performance-based methods for selecting events with maximal unmet demand does not outperform the other methods, it does have strong performance, and a study that uses this approach would be viable.

D-Optimal, S-Optimal, and clustered selection approaches have performance similar to randomly selecting events. These methods demonstrate how finding a good sample attributes alone is challenging.

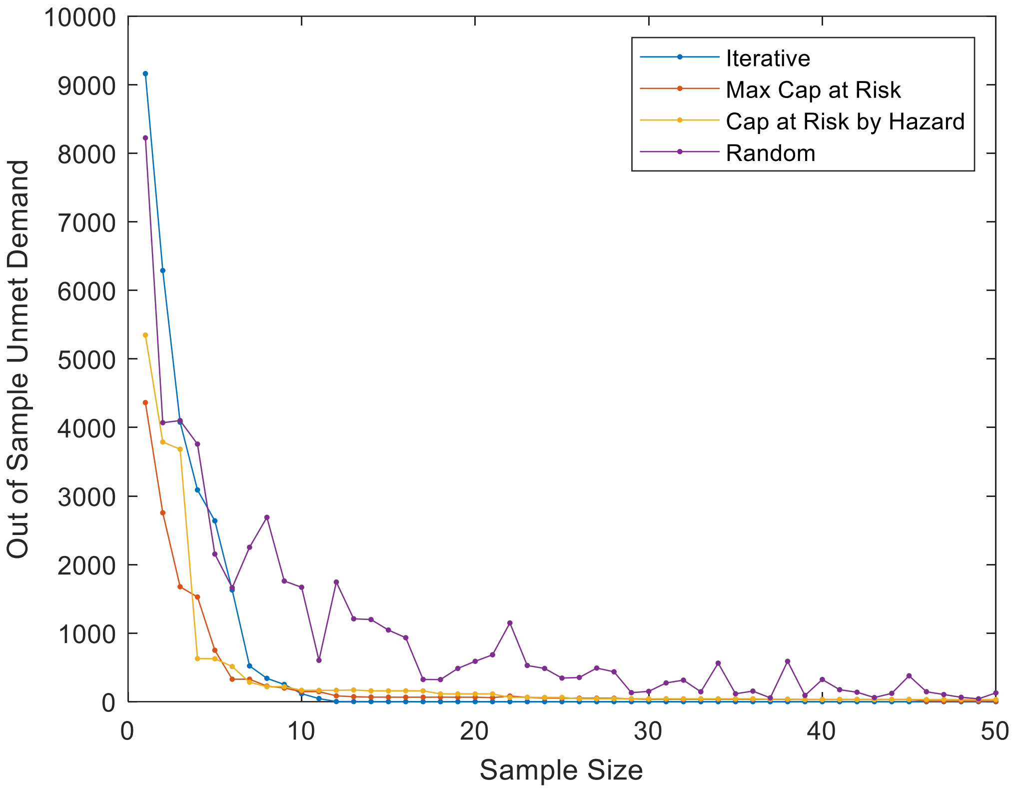

Figure 12: Out of sample performance of selected sampling methods. Shown here: iterative, maximum capacity at risk, maximum capacity at risk by hazard and asset category, and random event selection

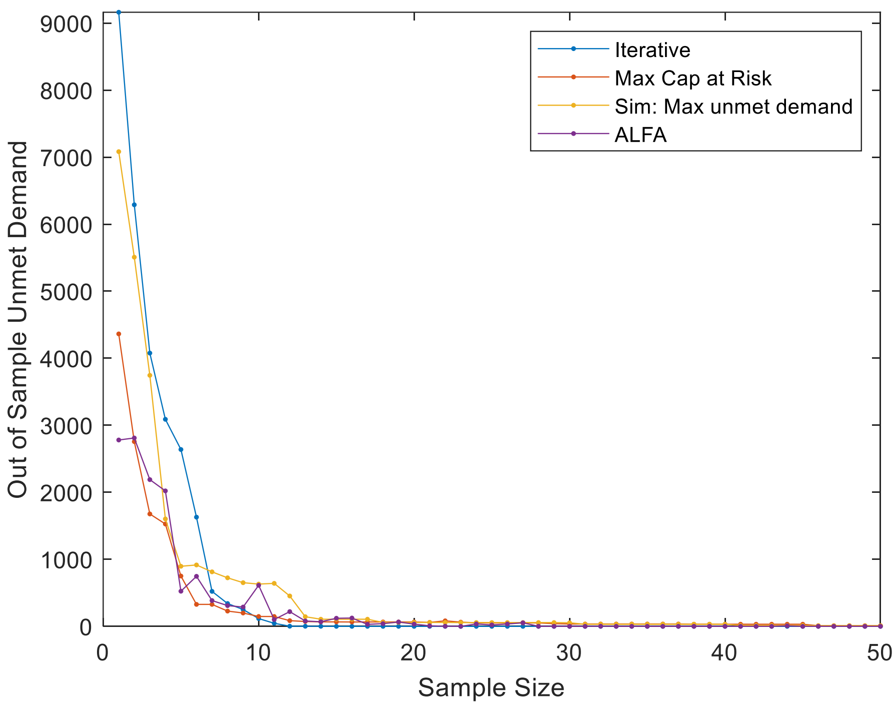

Figure 13: Out of sample performance of selected sampling methods. Shown here: iterative, maximum capacity at risk, maximum simulated unmet demand, and ALFA

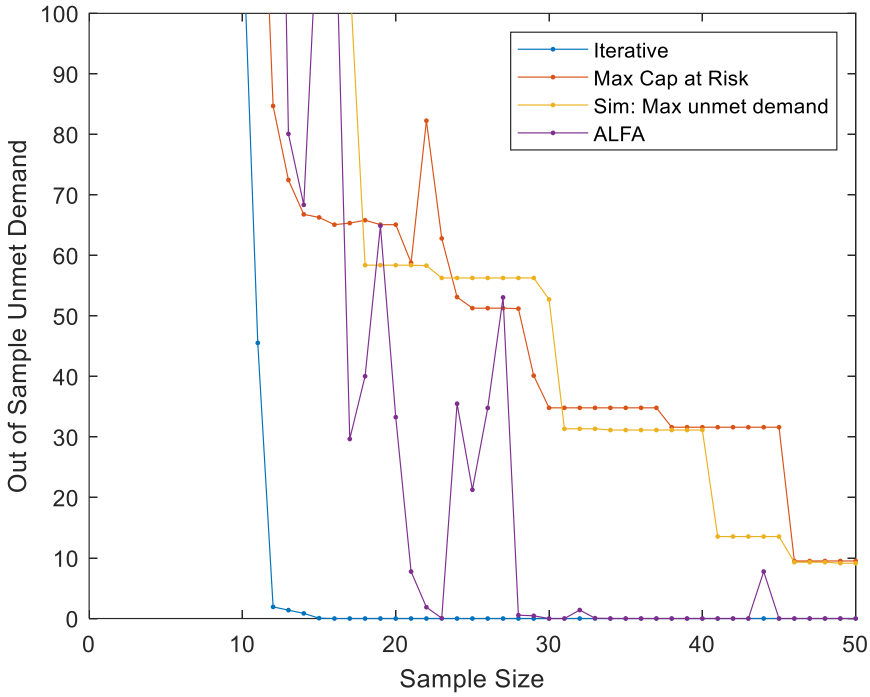

Figure 14: Same as above with Y-axis limit to show near optimal performance

Conclusions

Resilience planning is becoming an urgent planning necessity; fortunately, many resilience considerations can be integrated into existing planning models without excessive computational burden or unfamiliar modeling techniques. There are still challenges; sampling a small yet robust subset of events will likely require simulation or iterative optimizations. Additionally, hazard control constraints for transmission are not straightforward to apply and additional research is needed to explore methods to do so in a scalable manner.

The largest hurdle for planners is in developing climate scenarios, generating credible extreme events, and mapping those events to asset level disruptions. Large amounts of data, sophisticated weather modeling, and detailed investigations on asset-specific vulnerabilities and performance characteristic are needed both for existing and candidate assets. The potential protection and performance changes from hardening upgrades must also be synthesized within the planning model. The number of possible hazards is large and the scope of these studies may need to be broadened to capture relevant impacts. While simple test systems can be created without any significant obstacles, implementing the methods on real systems and integrating with other planning functions such as resource adequacy or network stability will require higher resolution data, and more model interactions than capacity planning studies have typically needed.

References

[1] "Climate READi." https://www.epri.com/research/sectors/readi (accessed Apr. 27, 2023).

[2] "Climate Change and the U.S. Electricity Sector: Guide for Climate Change Resilience Planning," U.S. Department of Energy: Office of Energy Policy and Systems Analysis, Sep. 2016.

[3] "Climate Change and the U.S. Energy Sector: Regional Vulnerabilities and Resilience Solutions," U.S. Department of Energy: Office of Energy Policy and Systems Analysis, Oct. 2015.

[4] P. Maloney *et al.*, "Research to develop the next generation of electric power capacity expansion tools: What would address the needs of planners?," *Int. J. Electr. Power Energy Syst.*, vol. 121, p. 106089, Oct. 2020, doi: 10.1016/j.ijepes.2020.106089.

[5] "Dominion Energy Climate Report 2021," Dominion Energy, 2021.

[6] "AEP's Climate Impact Analysis: Powering Forward to Net-Zero," American Electric Power, Mar. 2021.

[7] C. Raymond, "Seattle City Light Climate Change Vulnerability Assessment and Adaptation Plan," Seattle City Light, Feb. 2016.

[8] "2019 Integrated Resource Plan: Final Resource Plan," Tennessee Valley Authority, Knoxville, TN, vol 1, 2019.

[9] "Climate Change Adaptation and Resiliency Plan 2020 Update," Tennessee Valley Authority, Knoxville, TN, Jul. 2020.

[10] "Climate Change Resilience and Adaptation: Summary of 2020 Activities," Consolidated Edison Company of New York, New York, NY, Jan. 2021.

[11] "Order Adopting Storm Hardening and Resiliency Collaborative Phase Three Report Subject to Modifications," NYPSC (New York Public Service Commission), Albany, NY, Jan. 2016.

[12] "2021 Integrated Resource Plan," PacifiCorp, Portland, OR, vol 1, Sep. 2021.

[13] "Building a Resilient Energy Gulf Coast: Executive Report," Entergy Corporation, 2010.

[14] J. Bruzgul *et al.*, "Rising Seas and Electricity Infrastructure: Potential Impacts and Adaptation Options for San Diego Gas and Electric (SDG&E)," California Energy Commission, California's Fourth Climate Change Assessment CCCA4-CEC-2018–004, Aug. 2018.

[15] "Climate Change Vulnerability Assessment Pursuant to Decision 20-08-046," Southern California Edison, Rosemead, CA, May 2022.

[16] J. H. Eto, “Planning Electric Transmission Lines: A Review of Recent Regional Transmission Plans,” Lawrence Berkeley National Lab. (LBNL), Berkeley, CA (United States), LBNL-1006331Rev., Apr. 2017. doi: 10.2172/1351315.

[17] V. S. Budhraja, F. Mobasheri, J. Ballance, J. Dyer, A. Silverstein, and J. H. Eto, “Improving Electricity Resource-Planning Processes by Considering the Strategic Benefits of Transmission,” *Electr. J.*, vol. 22, no. 2, pp. 54–63, Mar. 2009, doi: 10.1016/j.tej.2009.01.004.

[18] “ISO Board Approved 2021-2022 Transmission Plan,” California ISO, Mar. 2022. [Online]. Available: http://www.caiso.com/planning/Pages/TransmissionPlanning/Default.aspx

[19] “20-Year Transmission Outlook,” California ISO, May2022. [Online]. Available: https://stakeholdercenter.caiso.com/RecurringStakeholderProcesses/20-Year-transmission-outlook

[20] Michael Jaske, “CEC Development of Higher Electrification Grid Planning Scenarios,” California Energy Commission, Jul. 2022. [Online]. Available: http://www.caiso.com/InitiativeDocuments/CECPresentation-2022-2023TransmissionPlanningProcess-Jul62022.pdf

[21] “Renewable Integration Impact Assessment,” MISO, Feb. 2021. [Online]. Available: https://www.misoenergy.org/planning/policy-studies/Renewable-integration-impact-assessment/#nt=%2Friiatype%3AReport&t=10&p=0&s=Updated&sd=desc

[22] “MISO Futures Report,” MISO, Dec. 2021. [Online]. Available: https://www.misoenergy.org/planning/transmission-planning/futures-development/

[23] “MTEP21 Addendum Long Range Transmission Planning Tranche 1,” MISO, Sep. 2022. [Online]. Available: https://www.misoenergy.org/planning/transmission-planning/long-range-transmission-planning/

[24] “PJM Regional Transmission Expansion Plan (RTEP),” PJM, Mar. 2022. [Online]. Available: https://www.pjm.com/library/reports-notices/rtep-documents

[25] N. Dumitriu and N. Rodak, “Market Efficiency Study Process and RTEP Window Project Evaluation Training,” PJM, Oct. 2020. [Online]. Available: https://www.pjm.com/-/media/planning/rtep-dev/market-efficiency/2020-me-study-process-and-rtep-window-project-evaluation-training.ashx

[26] “Western Assessment of Resource Adequacy,” Western Electricity Coordinating Council, 2022.

[27] J. L. Ho *et al.*, “Planning Transmission for Uncertainty: Applications and Lessons for the Western Interconnection,” Johns Hopkins University, Jan. 2016. [Online]. Available: https://www.ethree.com/wp-content/uploads/2017/02/Planning-for-Uncertainty-Final-Report.pdf

[28] “Exploring the Impacts of Extreme Events, Natural Gas Fuel and Other Contingencies on Resource Adequacy,” EPRI, Palo Alto, CA, 3002019300, 2021.

[29] “Technical Update on Risk Based Planning: Improving the Power Flow Scenario Selection Process,” EPRI, Palo Alto, CA, 3002024590, 2022.

[30] “Technical Assessment of Resiliency Metrics and Analytical Frameworks,” EPRI, Palo Alto, CA, 3002014571, 2018.

[31] “Exploring Resilience and Common-Mode Outages in Resource Adequacy and Planning,” EPRI, Palo Alto, CA, 3002021810, 2021.

[32] “Power System Supply Resilience The Need for Definitions and Metrics in Decision-Making,” EPRI, Palo Alto, CA, 3002014963, 2020.

[33] F. D. Munoz, B. F. Hobbs, J. L. Ho, and S. Kasina, “An Engineering-Economic Approach to Transmission Planning Under Market and Regulatory Uncertainties: WECC Case Study,” *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 307–317, Jan. 2014, doi: 10.1109/TPWRS.2013.2279654.

[34] Q. Xu and B. F. Hobbs, “Value of model enhancements: quantifying the benefit of improved transmission planning models,” *IET Gener. Transm. Distrib.*, vol. 13, no. 13, pp. 2836–2845, 2019, doi: 10.1049/iet-gtd.2018.6357.

[35] M. Webster, B. Zhao, J. Bukenberger, and S. Blumsack, “Transition to Low-Carbon Electric Power: Portfolios, Flexibility, and Option Value,” *Environ. Sci. Technol.*, vol. 56, no. 13, pp. 9583–9592, Jul. 2022, doi: 10.1021/acs.est.1c08797.

[36] F. D. Munoz, B. F. Hobbs, and J.-P. Watson, “New bounding and decomposition approaches for MILP investment problems: Multi-area transmission and generation planning under policy constraints,” *Eur. J. Oper. Res.*, vol. 248, no. 3, pp. 888–898, Feb. 2016, doi: 10.1016/j.ejor.2015.07.057.

[37] Y. Liu, R. Sioshansi, and A. J. Conejo, “Multistage Stochastic Investment Planning With Multiscale Representation of Uncertainties and Decisions,” *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 781–791, Jan. 2018, doi: 10.1109/TPWRS.2017.2694612.

[38] S. Park, Q. Xu, and B. F. Hobbs, “Comparing scenario reduction methods for stochastic transmission planning,” *IET Gener. Transm. Distrib.*, vol. 13, no. 7, pp. 1005–1013, 2019, doi: 10.1049/iet-gtd.2018.6362.

[39] B. Zhao, J. Bukenberger, and M. Webster, “Scenario Partitioning Methods for Two-Stage Stochastic Generation Expansion Under Multi-Scale Uncertainty,” *IEEE Trans. Power Syst.*, vol. 37, no. 3, pp. 2371–2383, May 2022, doi: 10.1109/TPWRS.2021.3121369.

[40] J. P. Bukenberger and M. D. Webster, “Approximate Latent Factor Algorithm for Scenario Selection and Weighting in Transmission Expansion Planning,” *IEEE Trans. Power Syst.*, vol. 35, no. 2, pp. 1099–1108, Mar. 2020, doi: 10.1109/TPWRS.2019.2942925.

[41] J. P. Bukenberger and M. D. Webster, “Latent Clustering Model for Co-optimization of Transmission and Generation Investments Under Uncertainty,” presented at the CIGRE, Paris, Aug. 2020. [Online]. Available: https://e-cigre.org/publication/SESSION2020_C5-301

[42] S. Blumsack and W. Su, “Joint Planning of Natural Gas and Electric Power Transmission with Spatially Correlated Failures,” presented at the Hawaii International Conference on System Sciences, Hawaii, Jan. 2022. [Online]. Available: http://hdl.handle.net/10125/79774

[43] L. L. Garver, “Transmission Network Estimation Using Linear Programming,” *IEEE Trans. Power Appar. Syst.*, vol. PAS-89, no. 7, pp. 1688–1697, Sep. 1970, doi: 10.1109/TPAS.1970.292825.

[44] “PRE-SW: Adaptive Coordinated Expansion Planning Tool (ACEP Tool) v1.0 Beta.” https://www.epri.com/research/products/000000003002024594 (accessed Apr. 27, 2023).