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INTEGRATED POWER SYSTEM EXPANSION PLANNING WITH DISTRIBUTED ENERGY RESOURCES UNDER DEEP UNCERTAINTY

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RESUMEN DE LA TESIS PARA OPTAR AL GRADO DE MAGÍSTER
EN CIENCIAS DE LA INGENIERÍA MENCIÓN ELÉCTRICA Y DE LA MEMORIA
PARA OPTAR AL TÍTULO DE INGENIERO CIVIL ELÉCTRICO
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PLANIFICACIÓN INTEGRADA DE LA EXPANSIÓN DE SISTEMAS ELÉCTRICOS CON RECURSOS ENERGÉTICOS DISTRIBUIDOS BAJO INCERTIDUMBRE PROFUNDA

La creciente adopción de los recursos energéticos distribuidos (DER) está transformando la planificación de los sistemas eléctricos. Estos activos, conectados a las redes de distribución, pueden brindar servicios de flexibilidad que impactan las decisiones de inversión en transmisión. Este trabajo investiga cómo la flexibilidad operacional derivada del control y agregación de los DER puede influir en la expansión de la transmisión. Dada la interacción de la flexibilidad proveniente de diferentes tecnologías, es crucial representar las incertidumbres con precisión para evitar sobreestimar o subestimar la flexibilidad de los DER. Se propone un modelo de planificación de la expansión estocástico multietapa que optimiza las inversiones en transmisión y almacenamiento y servicios de DER frente a restricciones operativas detalladas e incertidumbres de largo plazo modeladas en un arbol de escenarios. Los casos de estudio dentro del *National Electricity Market*, Australia (NEM) muestran que un modelo determinista puede sobrestimar la capacidad de los DER controlables para desplazar las inversiones en transmisión en las etapas iniciales. Por el contrario, el modelo estocástico propuesto proporciona una evaluación más moderada, manteniendo una estimación más constante del potencial de desplazamiento de la inversión en transmisión por los DER controlables.

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The massive uptake of distributed energy resources (DER) is transforming the way power systems are planned. Decentralised assets connected to distribution networks are beginning to coexist with traditional network devices in the technology mix, impacting the investment decisions of new large-scale assets due to the flexibility services the former can provide to the operation of the system. This work investigates how the operational flexibility from DER controllability can influence the expansion of transmission and storage. Given the interplay of different technologies, accurately representing uncertainties is essential to avoid over or underestimating the flexibility of DER. To address this challenge, a multi-stage stochastic expansion planning model is proposed. The model can optimise transmission and storage investments, and DER services against long-term uncertainties and detailed operational constraints. A four-stage scenario tree is employed to represent uncertainties and a Dantzig-Wolfe decomposition within a column generation approach is used to tackle computational challenges. Case studies within the Australian National Electricity Market (NEM) demonstrate that a deterministic model could overestimate the capability of controllable DER to displace transmission investments in the early stages. Conversely, the proposed stochastic model provides a more measured assessment, maintaining a steadier estimate of transmission displacement potential by controllable DER throughout various stages.

Para mi familia, esto es de ustedes

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Glossary

AC alternating current.

AEMO Australian Energy Market Operator.

CCGT combined-cycle gas turbine.

CHP combined heat and power.

DER distributed energy resources.

DG distributed generation.

DSM demand-side management.

DSO distribution system operator.

DW Dantzig-Wolfe.

EV electric vehicle.

FFR fast frequency response.

HILP high-impact low-probabilty.

ICT information and communication technology.

IEA International Energy Agency.

ISP Integrated System Plan.

LWR least-worst regret.

LWWR least-worst weighted regret.

MILP mixed-integer linear programming.

MSG minimum stable generation.

NEM National Electricity Market.

NSW New South Wales.

OCGT open-cycle gas turbine.

ODP optimal development path.

PFR primary frequency response.

PS pumped-hydro storage.

QLD Queensland.

QSSF quasi steady state frequency.

RMP restricted master problem.

SA South Australia.

SFR secondary frequency response.

TAS Tasmania.

TSO transmission system operator.

UC unit-commitment.

VIC Victoria.

VPP virtual power plant.

VRE variable renewable energy.

Chapter 1

Introduction

1.1. Motivation

In the transition towards sustainable and low-carbon power systems, the effective integration and planning of renewable generation, transmission, and energy storage technologies becomes imperative in pursuing goals set by global and national organisations to reach *net zero* emissions [1]. Furthermore, with the massive uptake of distributed energy resources (DER), decentralised assets connected to distribution networks are beginning to coexist with conventional devices in the technology mix of power systems, changing how these are operated and planned. In this vein, an adequate coordination of DER can play a key role in the operation and planning of low-carbon power systems by providing flexibility services. Thus, the coordination of DER represents a significant opportunity to accelerate the pace of the energy transition by harnessing its flexible capabilities in order to achieve affordable, secure and reliable power systems [2].

Specifically, properly integrating and coordinating the flexibility provision from dispatchable DER could impact net demand growth as well as peak load and, consequently, the need for investments in utility-scale assets. This can occur by displacing or deferring requirements for new network infrastructure, particularly in transmission lines [3], utility-scale energy storage and generation [4], underscoring a considerable impact on costs for stakeholders and customers. However, the deployment of DER has significant uncertainty, and adequately assessing it is key to avoid the risk of over- or under-valuing the flexibility these technologies can provide. Remarkably, neglecting detailed operational constraints and uncertainties could result in sub-optimal or even infeasible decisions under a constantly evolving context if inadequate decision-making frameworks are employed [5, 6].

In this vein, it is crucial to understand the real-world implications and assess the value and impact of flexible DER in economically displacing utility-scale investments, considering different operational modes, detailed models of system operation, and long-term uncertainties. For example, the Australian system operator's most likely scenario for 2050 envisions a five-fold increase in distributed storage and generation, 60% completion of coal unit retirements by 2030, and a nine-fold increase in utility-scale variable renewables [7], highlighting the need for stochastic decision-making tools that can consider and manage a broad mix of flexible technologies emerging from different sources, at various scales [6, 8, 9] and across multiple scenarios. Such tools are essential for effective and anticipatory infrastructure planning that can accommodate resources to deal with power systems' evolving variability and uncertainty.

1.2. Hypothesis

This research proposes that a multi-stage stochastic planning model can provide a more accurate assessment of the ability of distributed energy resources (DER) to displace investments in utility-scale system infrastructure by considering a broad range of uncertainties and detailed operational constraints. A stochastic approach would enable robust, safer, and anticipatory investment portfolios compared to deterministic and stylised models, which could under- or over-estimate the flexibility provision from DER, leading to sub-optimal investment decisions.

1.3. Objectives

1.3.1. General objective

The general objective of this thesis is to assess and study the impact of the flexibility from distributed energy resources (DER) on the decision-making of large-scale infrastructure projects under conditions of deep uncertainty. To achieve this objective, a stochastic framework for power system expansion planning that incorporates an analytical model to represent distributed energy resources is proposed.

1.3.2. Specific objectives

- Integrate an aggregated analytical model for distributed energy resources within a stochastic framework for expansion planning under uncertainty.
- Co-optimise transmission and storage investments across multiple scenarios with different DER penetration levels within a real instance of the Australian National Electricity Market (NEM).
- Analyse the economic benefits perceived in terms of expected costs and costs by scenario when enabling the controllability of DER to provide demand-side flexibility for the operation and planning of power systems.
- Quantify, in terms of the investment probability and range of installed capacity, the impact of enabling the controllability of DER on the optimal investment portfolios of transmission and energy storage across multiple real scenarios of a transmission system operator.

- Showcase the advantages of utilising a stochastic model for the expansion planning of power systems when including DER within the dispatchable technologies by comparing the investment and total costs with a deterministic model.

1.4. Structure of the document

The remainder of this thesis is structured as follows. Chapter 2 presents a review of the state of the art regarding power system expansion planning with particular attention to the integration of demand-side technologies, challenges and current practices. Chapter 3 shows the methodology of this work, which is divided into the proposed mathematical model and the solution algorithm employed. Chapter 4 details the case study applications and input data. Results and discussion are presented in Chapter 5. Chapter 6 presents the conclusions and further work.

Chapter 2

Literature Review

This chapter delves into the state-of-the-art regarding the integration, impact, and modelling of DER on the expansion planning of low-carbon power systems. The topics covered in this chapter include a review of the role of DER in enhancing power system flexibility and the current practices and techniques for modelling their aggregation and controllability in planning studies. The chapter further provides a comprehensive overview of academic and industry practices for power system expansion planning, encompassing the representation and management of uncertainties in the planning process.

2.1. Participation of DER in power systems

Power systems worldwide are undergoing a significant transformation driven by the increasing levels of diverse devices connected to the grid [7]. Many of these resources are being connected to distribution systems in the form of DER rather than the transmission network, as has been the convention in the past. In this way, the increasing penetration of DER, along with technologies that enable their orchestration and control, is significantly impacting power system planning. As a result, new methodologies and tools are needed to plan the future power system infrastructure incorporating an increasing penetration of DER.

DER can include a range of different devices installed to generate, store, or consume energy at various locations. Common examples include distributed generation, electric vehicles (EVs), at-home batteries, and smart appliances, such as schedulable air conditioning or CHP units. A particular subset of these are *active* DER [10], which can be dispatched in response to either a market signal or a change in market conditions, providing flexibility for the system operation. For example, an active battery located in a household can almost instantaneously switch between supplying electricity to the house and drawing power from the main grid.

If the flexibility of active DER can be coordinated, it has the potential to support the energy transition by facilitating access to a broader pool of clean energy (e.g. energy produced by solar PV and stored in a household battery), enhancing power system reliability, and reducing costs for consumers. In particular, for DER to enhance power system operation, centralised systems need to be in place to coordinate and control resources on behalf of its owners to operate as a single entity. In this vein, by enabling a centralised operation of flexible DER, the operation of power systems can be altered because demand-side flexibility impacts net demand growth as well as peak load, modifying new network infrastructure requirements [4].

2.1.1. Operational flexibility provision in power systems

The concept of operational flexibility is defined in [11] as the technical ability of a component within a system to regulate its power exchange with the grid over time. From a system perspective, the IEA [2] defines flexibility as the ability of a power system to reliably and cost-effectively manage the variability and uncertainty of the demand and supply across all relevant timescales, from ensuring instantaneous stability of the power system to supporting long-term security of supply.

Moreover, a definition of the flexibility provision from aggregated DER is presented in [12]. The authors characterise flexibility as the aggregated components' capacity to modify their power exchange with the grid within a specified time interval and expressed in terms of a four-dimensional vector. In a general sense, flexibility in power systems can be understood as the ability of the system or a component within the system to manage the variability and uncertainty of load and generation through upward or downward regulation of its power exchanges over time.

The requirements for operational flexibility in power systems emerge mainly from the need to balance deviations and disturbances from the load as well as from conventional and intermittent generation and different types of outages that cause power flow imbalances [11]. Therefore, as power systems transition to a low-carbon setting, more system flexibility allows for a safer and cost-effective VRE integration, as operators have greater capabilities to re-balance instantaneous power disturbances and reduce curtailment. Moreover, in the long term, system operators must ensure sufficient flexibility is available in such a manner that operation is feasible with significant levels of intermittent generation.

The flexibility in power systems can be provided by generation, both conventional and distributed, and by other resources available in the system, which include utility-scale and distributed energy storage systems (ESS), conventional (e.g. heating and cooling) and new loads (e.g. electric vehicles) with greater controllability, interconnections and network infrastructure, and even by other energy sectors able to interact with power systems through different energy carriers. Figure 2.1 summarises the primary sources of flexibility for power systems and their interactions.

In particular, as the number of new devices being connected to the distribution systems in the form of DER grows, the demand side has significant potential to contribute with enhanced flexibility to power systems. While DER have several benefits for individual customers, from a system perspective, they also have the potential to be aggregated together and leveraged to provide flexibility services at the local and bulk power system levels [13]. From responding quickly to reductions in supply to following price signals to adapt demand profiles, the orchestration of loads and devices through aggregators can provide new levels of operational flexibility for power systems.

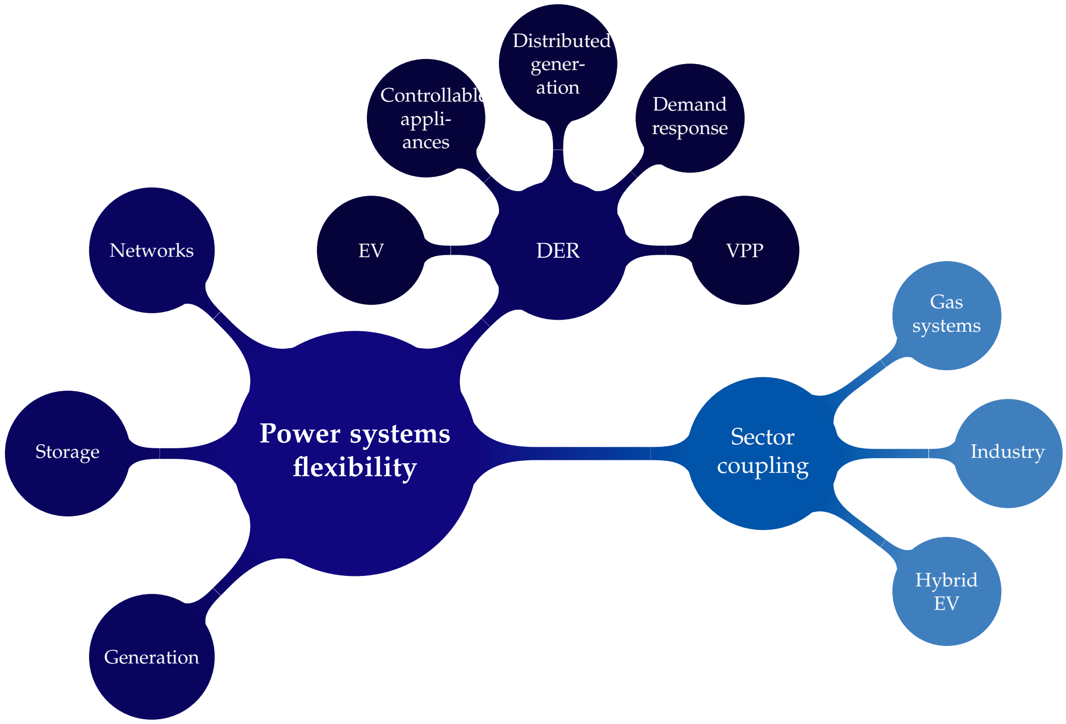


Figure 2.1: Flexibility sources in power systems.

The orchestration of distributed energy resources is mainly carried out through aggregators, which are entities that can participate in various electricity markets by providing services to the power system [14]. The primary goal of the aggregation is to enable a group of diverse resources (consumers, producers, prosumers or any combination thereof) to appear to a system or a market operator as a single, unified entity [15].

Aggregators establish contracts with individual demand-side participants (residential, commercial, and industrial customers) and aggregate their devices to operate as a single unit to provide network services. These aggregated pools often comprise a mix of different types of loads and devices (e.g., distributed storage and generation) to maximise their ability to provide flexibility to the system and generate revenues from it.

Figure 2.2 illustrates aggregators' core components and structure, which comprise a blend of centralised and decentralised control and IT systems. Data related to weather forecasts, wholesale electricity prices, and overall power supply and consumption trends are processed and shared through communication networks to optimise the operation of the dispatchable DER associated with the aggregator [16].

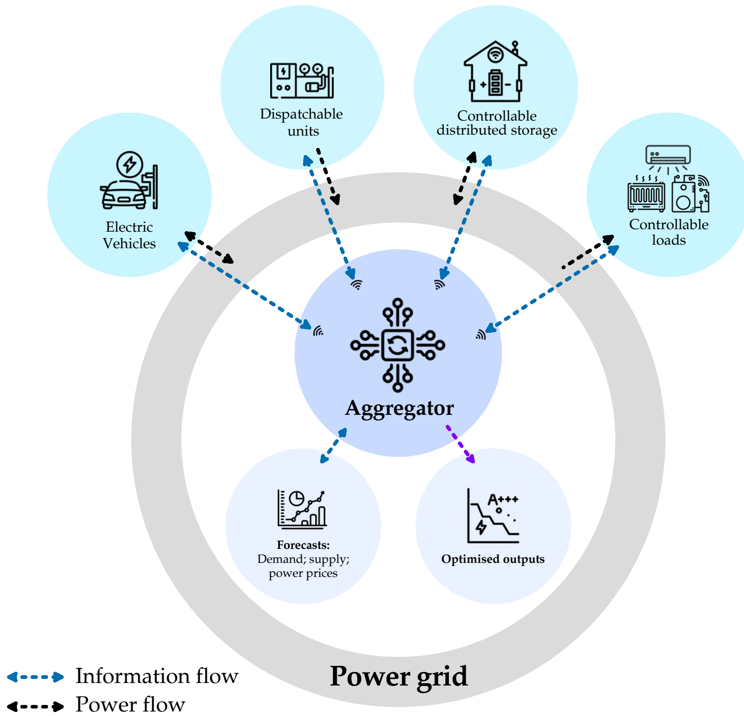


Figure 2.2: General schema of aggregators in power systems.

In response to the growing penetration of DER and to capitalise on the potential benefits that their aggregation and flexibility offer to the system, two main aggregation frameworks have emerged to foster the participation of the DER in electricity markets: the demand response programs and the virtual power plants (VPP). Both frameworks utilise advanced control and communication technologies to enhance the controllability and visibility of multiple electric devices within the power grid, such as distributed batteries and electric vehicles (EVs).

Demand response programs enable the management of various controllable and schedulable loads through various customer incentives. These programs can provide load reduction and shifting services, with the primary objective of modifying the usage patterns of electrical loads of different types. Typical applications include domestic appliances and commercial or industrial facilities, where optimising usage patterns can reduce energy production and utilisation costs, enhance system reliability, and improve the grid's hosting capacity.

Virtual power plants are networks that aggregate decentralised generation units, storage systems and even flexible loads. VPPs optimise the aggregation of distributed resources across vast areas by employing data-driven techniques and information and communication technologies ICTs. They also participate in multiple markets, such as wholesale energy and frequency ancillary services, to provide various network services [17, 18]. Given their structure and technical configuration, VPPs can also offer and manage demand response services.

Therefore, distributed energy resources, particularly those with aggregation capabilities, present a significant opportunity for power system operation in both technical (security and reliability) and economic terms. Moreover, these operational benefits hold the potential to translate into changes in the transmission design stages, primarily by targeting the reduction of investments in transmission redundancy or reinforcements, thereby minimising the risk of stranded assets.

2.1.2. Integration and modelling of DER in power system planning

As introduced in the previous section, the increasing deployment of DER on the demand side could unlock valuable opportunities to enhance power system flexibility. This trend requires a shift in expansion planning models, as these must now account for DER alongside traditional dispatchable resources. Developing new planning frameworks at the transmission level is crucial to assess the impact of large-scale DER deployment at the distribution level and its subsequent implications for the transmission grid expansion requirements.

In particular, [19] points out the potential impact of DER technologies in the future development of the power systems, highlighting that their inclusion within the expansion planning tasks will result in changes in the optimal portfolios for grid-scale assets like transmission lines. In response to this problem, various studies have proposed diverse models and analysed the impact of incorporating different DER technologies into long-term planning frameworks.

Using two-stage stochastic models, the authors in [20, 21] explore the impact of demand-side participation on system planning. Their models co-optimise investments in transmission, storage, and generation with the allocation of demand response and reserves while leveraging Conditional Value-at-Risk (CVaR) as a risk assessment metric under various scenarios. The findings reveal that load shifting facilitates a higher investment of VRE and enhances operational flexibility under risk-averse conditions by reducing total costs. Notably, flexible technologies are highly valued by risk-averse decision-makers. Still, their impact is non-linear, leading to investments in utility-scale assets, particularly when flexibility is readily available at a low cost.

In [3], a two-stage model employing distributionally robust optimisation is proposed to analyse the impact of integrating active DER into the expansion planning problem. The proposed framework leverages DER, particularly through a modelling via aggregators to schedule corrective control services (load increase, load reduction and load shifting) in response to uncertainties arising from various contingencies. The results demonstrate that the increased flexibility provided by DER enables the utilisation of latent capacity in existing transmission assets, thereby deferring the need for new investments. Additionally, in [22], the model is further used to highlight the advantages of DER in mitigating the impact of HILP events, like earthquakes, ultimately reducing the need for network reinforcements.

The impact of smart charging schemes for EVs in the expansion planning problem is studied through a deterministic model applied to the Chilean power system in [23]. The analysis highlights that higher EV penetration encourages investments in solar generation due to the additional system flexibility provided. This increased flexibility allows for reducing peak load by spreading charging requirements throughout early morning and mid-day.

Regarding distributed generation (DG), various studies [24, 25] have investigated the impact of incorporating DG as an active resource within the distribution planning problem. Their findings demonstrate that DG can defer line reinforcements in distribution networks, depending on its size, location, and type. However, these studies do not assess the impact of DG inclusion on transmission expansion planning. In [26], the effects of DG are studied through an AC optimal power flow in the transmission network of Queensland, Australia. The research concluded that distributed photovoltaics have a greater effect on transmission deferral than wind generators due to their higher deployment capacity across diverse areas.

In [27], the authors show evidence that distributed generation alone has a limited effect on deferring transmission investments. They propose that distributed generation must be complemented by flexible resources like storage or demand response programs to significantly reduce or delay investments in utility-scale assets. This highlights the potential of diverse, active DER deployments to enhance the temporal capabilities of distributed generation for producing and storing energy, thereby altering the need for new transmission network investments.

The modelling and impact of DER in power system expansion planning is further studied in [28] through a deterministic bi-level model. This study presents a framework for the TSO-DSO coordination to quantify the value and impact of local flexibility services offered by microgrids in the expansion and operation of the system. The results demonstrate a shift in investment plans, reducing investment and operational costs by utilising DER flexibility services.

While the reviewed works contribute significantly to model, assess, and demonstrate the impact of incorporating active DER into the planning process, these fall short of simulating a planning process over a more granular time and uncertainty representation required for this task (i.e., more representative days and more epochs). This is particularly concerning, given the extended lead times of transmission lines and the need to understand the impact of different storage durations.

Furthermore, power system planning processes are inherently susceptible to diverse uncertainties, encompassing demand growth, variable renewable energy (VRE) deployment, fuel and investment costs, and, most recently, the retirement of coal generation units [29]. Under such conditions, utilising existing models in the literature can lead to suboptimal decisions due to limitations in long-term modelling capabilities and the lack of robust uncertainty management strategies.

Moreover, DER are evolving technologies subject to long-term uncertainties related to their deployment and coordination. These uncertainties require modelling capable of anticipating diverse trajectories associated with their development over a long time window. Therefore, adequate modelling would enable more accurate quantification of the impact of DER on the investment dynamics of other power system assets like utility-scale storage and transmission lines, both in the short and long term, thus minimising the risk of investment inefficiencies.

2.2. Experiences and practices in planning low-carbon power systems

Driven by *net-zero*, the decarbonisation targets and the rapid integration of non-conventional and variable generation technologies, the power system planning task has recently become significantly more complex. This heightened complexity stems from the growing uncertainty surrounding new network participants, including their timing and location of connection. Consequently, planners face the challenge of designing an optimal infrastructure development path that balances security, reliability, and cost minimisation for a rapidly evolving system amidst significant long-term uncertainty. However, these infrastructure investments may carry significant risks, such as the potential of stranded assets, owing to their long lifetimes and irreversibility. Therefore, careful evaluation of such investments is necessary. [30].

Furthermore, the complex and evolving uncertainties that affect power system planning require the development of new methods to identify more cost-effective and less risky infrastructure investment and development pathways. This section discusses recent advances in power system planning frameworks, focusing on adaptive and flexible methodologies that take into account a wide range of infrastructure options.

2.2.1. State of the art in power system expansion planning

Investment flexibility is a new element to consider in the expansion planning of power systems. This concept refers to how different investment options whose technical, locational, operational and/or procurement characteristics allow them to act as compromise solutions capable of adapting and providing value across various scenarios, naturally hedging against planning uncertainty. Recent studies, such as those in [31, 32], have explored this concept by providing insight regarding accurately representing uncertainties and investment decisions to capture this flexibility. A crucial part of capturing investment flexibility is to represent the operational flexibility of the various assets, whether they are existing or potential candidates [33].

To accurately assess the flexibility in the system's operation, it is crucial to have a planning model that represents the strengths and limitations of individual units. This modelling approach includes understanding the technical constraints of thermal synchronous units and energy storage of different types. Several authors have explored the impact of various models of operational flexibility on expansion planning. Studies like [34, 35] have investigated the effect of operational flexibility on designing a generation portfolio. Other works such as [36–39] have modelled operational flexibility to determine whether it is appropriate to invest in transmission and storage assets.

Recent advancements in multi-stage stochastic expansion models have incorporated higher levels of operational detail to capture the benefits of flexible technologies such as storage more accurately. Various works [6, 8, 9, 40] demonstrate this trend by analysing the influence of long-term uncertainties on optimal investment portfolios for transmission, generation, storage, and smart grid technologies. In particular, [8] argues that a more detailed representation of uncertainties within the scenario tree utilised in modelling the future can unlock increased value for critical and flexible investment options.

Following this trend, [40] investigates the impact of using a multi-stage stochastic planning model for the expansion of the Australian system. The study compares investment portfolios obtained by employing this model with those derived from a deterministic approach like LWWR. The work highlights the cost-effectiveness of investment portfolios generated via a stochastic model. Moreover, it emphasises the reduced cost of high-risk scenarios, further underscoring the importance of models that incorporate diverse uncertainties and operational details to identify the option value of different candidate technologies.

However, increased operational detail leads to a higher computational burden because of the need for more constraints and a comprehensive representation of the operation. In a two-stage generation expansion problem, [41] examines the impact of unit commitment constraints (UC) using a multi-cut Benders decomposition. Several reviews [42–45] have also highlighted research efforts to incorporate operational flexibility in generation and transmission expansion modelling.

Including complex operational constraints within highly detailed models, particularly in the context of expansion planning under uncertainty, when stochastic models are employed, creates large monolithic problems. Advanced decomposition techniques have become crucial in addressing the intractability of such large MILP models. Recent advancements in Dantzig-Wolfe (DW) decomposition and column generation algorithms offer promising solutions for handling these complexities. For instance, [46] employs variable splitting in the column generation algorithm to solve a multi-stage stochastic capacity problem. The work [47] incorporates UC constraints into the operational problem for solving a generation expansion problem. Furthermore, [9] enhances the algorithm with a column-sharing approach to tackle the common issues of the column generation algorithm.

In [8], the same approach is applied for the joint expansion of transmission and storage in a real instance of the Australian system. Integrating gas network constraints into a stochastic planning problem is also investigated in [48]. [49] presents a welfare-maximising approach for transmission capacity expansion considering an oligopoly, using column generation to solve the problem. Finally, [6] emphasises the need for computationally efficient methods to address non-convexities arising from high operational details, paving the way for fully capturing the benefits of smart grid technologies in real applications for planning problems.

2.2.2. Management and representation of uncertainty in power system planning

2.2.2.1. Sources of long-term uncertainty in power system planning

When dealing with long-term planning of power systems, identifying the sources of uncertainty that will condition the system's needs is of utmost importance. Any power system is heavily influenced by changes in energy policy, the development of new technologies and the evolution of new business models. All these changes lead to high and growing uncertainty and, therefore, to modifications to the configuration of the system's operation. This section reviews the main uncertainty sources influencing expansion planning [29, 30, 50].

Load growth and VRE deployment are two major parameters that create uncertainty in power system planning. Load growth refers to the changes in demand patterns due to the electrification and the introduction of new technologies, which produce high levels of uncertainty in the 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). VRE deployment is mainly associated with the penetration levels of VRE, which are encouraged by energy policies and cost reduction and are further affected by the higher adoption of DER in some countries, changing the traditional view of the distribution network as a passive element within the system.

The growth of commercial technologies can be a source of uncertainty due to the high investment costs and long lead times required to implement changes in the network. However, the emergence of new technologies such as demand-side management (DSM) and battery storage can result in reduced investment costs and shorter lead times compared to traditional infrastructures. However, these have a higher dependence on the system's operation, creating issues when comparing these two types of assets (traditional heavy infrastructure versus non-network solutions), as well as having a high dependency on the regulatory framework associated with the system operator.

Many countries continuously revise energy policies and regulations, creating a significant source of long-term uncertainty. This uncertainty mainly affects the cost of certain technologies due to the support provided to their development through subsidies or taxes. In regions with high decarbonisation targets, the power market structures and mechanisms are undergoing continuous revision, which could have crucial impacts on the economic dispatch and power flows. Recently, new technologies have triggered the emergence and study of new markets, such as the very fast FCAS market in the NEM, Australia [51], which encourages the operation and dispatchability of battery storage.

Changes in the generation mix of power systems are a significant source of long-term uncertainty. This is due to new inverter-based technologies being introduced to power systems worldwide, leading to a change in the generation mix in most regions. This shift may be driven by policies, extreme events, new ancillary services requirements in the presence of renewables, and asynchronously connected resources (e.g. requirements for faster frequency response and minimum system inertia), among other factors. Additionally, the timing of the retirement of coal units is both highly uncertain and critical to determining the optimal investment portfolio for the current and future network.

Investment costs and fuel prices are two critical sources of uncertainty in power systems. The cost of new technologies significantly influences investment decisions, as it may change the optimal investment options for portfolios and assets needed for the development of new resources in the next few years. Natural gas prices are also a significant source of uncertainty. The price of gas determines the economic dispatch, which, in turn, affects the operational flexibility of the system.

Finally, weather and climate change are significant challenges on the horizon. Extreme events such as heatwaves, wildfires, and other unexpected natural disasters are becoming more frequent and severe, affecting power systems. Additionally, the low availability of water for both hydropower generation and cooling in thermal generation is another persistent effect that is increasingly common as the climate changes. As a result, planners need to anticipate multi-contingency events caused by climate uncertainty rather than just failures of a few components.

2.2.2.2. Impact and representation of deep uncertainties in decision-making for power systems

Having reviewed the need for investment flexibility and the main sources of uncertainty in power system planning, it is important to understand how to adequately represent both concepts in planning studies to capture their impact on expansion decisions.

In general, the decision-making process behind the deployment of new infrastructure focuses on incorporating details on the representation of the system's operation and information associated with future scenarios. Additionally, the uncertainties surrounding the planning process pose a challenge, given that it is difficult to agree on the relationships between the main uncertainties and risks for the long term. Moreover, decision-making in the context of deep uncertainty requires an approach that aims to prepare and adapt the system against uncertain events by monitoring how the future evolves, allowing adaptations over time as uncertainties unfold and knowledge is gained, with the objective to implement adaptive and robust long-term strategies [52].

The literature describes situations where deep uncertainties are present, all agreeing on certain common elements. In these situations, following the definition presented in [53], experts may not know, or decision-makers may not be able to agree on (1) the appropriate models to describe the interactions among a system's variables, (2) the probability distributions to represent uncertainty about key parameters in the models, and/or (3) how to value the desirability of alternative outcomes.

Furthermore, [54] defines deep uncertainty as the presence of at least one of the following three elements: (1) multiple possible future states of the world without known relative probabilities, (2) multiple divergent but equally valid world views, including values used to define criteria of success, and (3) decisions that adapt over time and cannot be considered independently. Similarly, deep uncertainty is defined in [52] as situations in which experts do not know or the parties to a decision cannot agree upon (1) the external context of the system, (2) how the system works and its boundaries and (3) the outcomes of interest from the system and/or their relative importance.

Following these definitions, it is relatively evident that the decision-making process in power system planning is directly affected by deep uncertainties. This is due to the complexity involved in (1) defining and reaching an agreement on the probabilities associated with potential future scenarios and system contexts, (2) the existence of different interpretations of the potential futures that the system may encounter as knowledge is gained and uncertainties unfold, and (3) the need of making flexible, adaptive and robust investment decisions, which are subject to considerable interdependence.

Thus, deep uncertainties and the need to adequately represent investment flexibility already represent a substantial challenge. To cope with this situation, different modelling assumptions are made regarding how projects are implemented and managed and how risks and uncertainties are incorporated. As described in [32, 55], the decision-making process could be modelled under one of the following approaches:

- **Deterministic approach**: Discounted cash flows are utilised to evaluate the best course of action regarding an investment opportunity, considering a binary decision on whether to proceed with a project. The project will persist even if it generates negative cash flow in the future, and the risks are factored into the discount rates applied to estimate future income and expenses.

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

Another crucial aspect of power system planning is representing the future, which involves considering uncertainties to identify the optimal development path for the system. This process entails identifying relevant uncertain parameters and creating a set of scenarios describing potential futures. These scenarios interact with decision-making processes, often employing decision trees for stochastic optimisation, which helps determine different stages of decisions based on how uncertainties unfold over time.

The amount and use of information are critical to understanding and representing investment flexibility. It is essential to determine what information is handy for making decisions, balancing the need for comprehensive data with the resources required to process it. Efficiently using information helps reduce costs and risks while enhancing investment flexibility.

Decisions in power system planning are divided into two groups: first-stage *(here-and-now)* decisions, made before uncertainty unfolds, and second-stage *(wait-and-see)* decisions, made after uncertainty unfolds. First-stage decisions often involve investment decisions, while second-stage decisions pertain to operational aspects like generator outputs and load shedding. These two stages represent states of uncertainty and are independent of the time periods considered in the problem. The two-stage approach is commonly used to handle decisions under uncertainty and can cover multiple years. However, it may not capture all the flexibilities required in real-world investment problems. A multi-stage decision process, where decisions are updated as the future unfolds, could provide a more comprehensive approach. This method allows for adaptive decisions that accommodate real investment options, enhancing flexibility by considering multiple decision points as uncertainties are resolved.

Despite its advantages, multi-stage modelling creates increased computational complexity due to the interdependence of decisions across stages, leading to large problem sizes that are difficult to analyse exhaustively. Two primary methodologies are used for this type of problem: multi-stage stochastic approaches and multi-stage Least Worst Regret (LWR) approaches. The stochastic approach is well-established and scalable for large problems, incorporating risk measures to align with risk aversion requirements. The LWR approach, while effective, faces challenges like the curse of dimensionality, making it complex to implement.

The multi-stage decision problem framework offers increased and enhanced assessment of investment flexibility, allowing for more efficient system development. Each approach has advantages and disadvantages, but incorporating multi-stage modelling into power system planning is essential for making adaptive and informed decisions as uncertainties unfold.

2.3. Contributions

Given the preceding literature survey, the main contributions of this work are the following:

- Development of a multi-stage stochastic power system expansion planning framework incorporating a comprehensive model for flexible technologies (DER), accounting for demand response and distributed storage as virtual power plants (VPP), and its operating modes (controllable and non-controllable) within a detailed system operation under uncertainty.
- Analysis and quantification of the impact of DER and its operating modes on displacing system investments over time and across scenarios from a techno-economic perspective in a real system, showing the need to account for uncertainty representation in expansion planning to adequately value DER.
- Assessment of how the choice of the model setting, whether multi-stage stochastic or deterministic, impacts the anticipatory capacity of investment decisions when incorporating DER controllability into a long-term expansion planning framework.

Chapter 3

Methodology

Nomenclature

Sets of indices

$a \in \mathcal{A}$	Areas in the system
$b \in \mathcal{B}, \mathcal{B}_a$	Buses in the system, in area a
$d \in \mathcal{D}, \mathcal{D}_b$	DER in the system, in bus b
$d \in \mathcal{D}^0, \mathcal{D}^{\mathrm{c}}$	Existing, candidate DER
$e \in \mathcal{E}, \mathcal{E}_a, \mathcal{E}_b$	ESS in the system, in area a, in bus b
$e \in \mathcal{E}^0, \mathcal{E}^{\mathrm{c}}$	Existing, candidate ESS
$g \in \mathcal{G}, \mathcal{G}_a, \mathcal{G}_b$	Synchronous generators (including hydro) in the system, in area a, in bus b
$g \in \mathcal{G}^{\mathrm{H}}$	Hydro generators in the system
$g \in \mathcal{G}^{\mathrm{R}}$	Reservoir generators in the system
$j \in \mathcal{K}_n$	Indices of elements in $\mathcal{Z}_n$
$l \in \mathcal{L}$	Transmission lines in the system
$l \in \mathcal{L}_b^{\mathrm{from}}, \mathcal{L}_b^{\mathrm{to}}$	Transmission lines departing from, arriving to bus b
$l \in \mathcal{L}^0, \mathcal{L}^c$	Existing, candidate transmission lines
$n \in \mathcal{N}$	Nodes in the scenario tree
$\mathcal{P}_n$	Predecessor nodes of node n, including node n
$g \in \mathcal{R}, \mathcal{R}_b$	Variable renewable generators in the system, in bus b
$t \in \mathcal{T}_w$	Hours within a representative period w
$w \in \mathcal{W}_n$	Representative periods, node n
$\mathcal{X}_n$	Feasible operational decisions, node n
$\mathcal{Z}_n$	Feasible total installed units, node n

Parameters

$\boldsymbol{A}_n$	Matrix linking operational and investment decisions, node n
$c_{n,g}^{\mathrm{fuel}}$	Fuel cost, node n, generator g [$/MW]
$c_g^{\mathrm{sup/sdn}}$	Startup/shutdown cost, generator g [$]
$c_d^{\mathrm{shup/shdn}}$	Cost for shifting load upward/downward, DER d [$/MW]

c_d^{rd}	Cost for voluntary load reduction, DER d [\$/MW]
$\boldsymbol{c}_n^{\mathrm{inv/op}}$	Vectors of investment/operational cost, node n
$D_{n,w,b,t}$	Total demand, node n, representative period w, bus b, time t [MW]
$\bar{E}_e$, $\underline{E}_e$	Maximum/minimum energy capacity, ESS e [MWh]
$\bar{F}_{l,t}/\underline{F}_{l,t}$	Maximum forward/reverse flow, line l, time t [MW]
$\mathscr{F}_g/\mathscr{P}_g$	Full/Partial outage rate, generator g [%]
$\mathrm{LL}_{n,a,t}$	Largest load contingency, node n, area a, time t [MW]
NT	Number of hours per representative period
N_g	Number of units, cluster g of generators
$\bar{P}_g/\underline{P}_g$	Maximum/minimum power output, generator g [MW]
$\bar{P}_g^{ty^+}$	Maximum capacity to provide upward frequency response type ty (pfr/sfr), generator/cluster g [MW]
$\tilde{P}_{n,g,t}^{\mathrm{R}}$	Available renewable energy resource, node n, generator g, time t [MW]
$\bar{P}_e^{\mathrm{ch/dch}}$	Maximum charging/discharging power, ESS e [MW]
$\bar{P}_e^{\mathrm{ffr}}$	Maximum capacity to provide FFR, ESS e [MW]
r	Financial discount rate
$\mathrm{R}_g^{\mathrm{up/down}}$	Up/downward ramp limit, generator/cluster g [MW]
RS_g	Frequency response slope, generator/cluster g
$\mathrm{T}_g^{\mathrm{up/dn}}$	Minimum up/down times, generator/cluster g [h]
$\mathrm{T}_g^{\mathrm{sup/sdn}}$	Startup/shutdown times, generator/cluster g [h]
$\mathrm{T}^{\mathrm{pfr/sfr}}$	Time window for primary/secondary frequency response provision [s]
$\mathrm{T}_d^{\mathrm{rec}}$	Re-balance window duration for load shifting, DER d [h]
VoLL	Value of Lost Load [\$/MW]
y_n	Number of years from node n to root node
$\bar{z}_{n,e}^{\mathrm{L}}$	Maximum capacity for investment, node n, line l
$\bar{z}_{n,e}^{\mathrm{E}}$	Maximum capacity for investment, node n, ESS e
$\bar{z}_{n,d}^{\mathrm{D}}$	Maximum capacity for investment, node n, DER d
$\bar{\boldsymbol{Z}}_n$	Vector of maximum total installed units, node n
α_g	Derating factor due to partial outage, generator g
$\bar{\gamma}_d^{\mathrm{shup/shdn}}$	Maximum upward/downward capacity load shifting, DER d [MW]
$\bar{\gamma}_d^{\mathrm{red}}$	Maximum capacity voluntary load reduction, DER d [MW]
Δf^{db}	Frequency response dead-band target deviation [Hz]
$\Delta f^{qssf^{-/+}}$	Target QSS frequency low/high events [Hz]
ζ_d	Payback effect penalisation, DER d [%]
$\eta_e^{\mathrm{ch/dch}}$	Charging/discharging efficiency, ESS e [%]
$\tilde{\kappa}_{d,t}$	Inflexible power exchanges, node n, DER d, time t [MW]
$\xi_{g,w}$	Capacity factor, hydro generator g, representative period w [%]
$\pi_{n,l}^{\mathrm{L}}$	Investment cost, node n, transmission line l [\$]

$\pi^{\mathrm{E}}_{n,e}$	Investment cost, node n, ESS e [$]
$\pi^{\mathrm{D}}_{n,d}$	Investment cost, node n, DER d [$]
ρ_n	Probability of occurrence, node n
σ_a	Load damping factor, area a
$\omega_{n,w}$	Weight of representative period w, node n

Variables and functions

$e^{\mathrm{E}}_{n,e,t}$	State of charge, node n, ESS e, time t [MWh]
$e^{\mathrm{sh/shup/shdn}}_{n,d,t}$	State of load shifting/shift up/shift down, node n, DER d, time t [MWh]
$f_{n,l,t}$	Power flow, node n, line l, time t [MW]
$f^{\mathrm{p/n}}_{n,l,t}$	Positive/negative slack, node n, line l, time t [MW]
$LS_{n,b,t}$	Load shedding, node n, bus b, time t [MW]
$n_{n,g,t}$	Commitment variable, node n, generator g, time t
$p_{n,g,t}$	Power output, node n, generator g, time t [MW]
$p^{\mathrm{cu}}_{n,g,t}$	Curtailed power, node n, generator g, time t [MW]
$p^{\mathrm{ch/dch}}_{n,e,t}$	Charging/discharging power, node n, ESS e, time t [MW]
$p^{s^{ty}}_{n,g,t}$	Power scheduled for frequency response service s (ffr/pfr/sfr), type ty (upward/-downward), node n, generator g, time t [MW]
$p^{s^{ty}}_{n,e,t}$	Power scheduled for frequency response service s (ffr/pfr/sfr), type ty (upward/-downward), node n, BESS/PS e, time t [MW]
$x^{\mathrm{L}}_{n,l}$	Integer variable for investment, node n, line l
$x^{\mathrm{E}}_{n,e}$	Integer variable for investment, node n, ESS e
$x^{\mathrm{D}}_{n,d}$	Integer variable for investmen, node n, DER d
$z^{\mathrm{L}}_{n,l}$	Total installed units, node n, transmission line l
$z^{\mathrm{E}}_{n,e}$	Total installed units, node n, ESS e
$z^{\mathrm{D}}_{n,d}$	Total installed units, node n, DER d
$\boldsymbol{X}^{\mathrm{inv/op}}_n$	Vector of investment/operation variables, node n
$\boldsymbol{Z}_n$	Vector of total installed units, node n
$\gamma^{\mathrm{shup/shdn}}_{n,d,t}$	Upward/downward load shift, node n, DER d, time t [MW]
$\gamma^{\mathrm{red}}_{n,d,t}$	Voluntary load reduction, node n, DER d, time t [MW]
$\delta^{\mathrm{sdn/sup}}_{n,g,t}$	Shutdown/startup node n, generator g, time t [MW]
$\Delta p^{gen/load\text{-loss}}_{n,a,t}$	Generation/load contingency size, node n, area a, time t [MW]
$\kappa_{n,d,t}$	Power exchanges, node n, DER d, time t [MW]
$\lambda_{n,j}$	Binary variable to select column j in node n
$\mu_{n,e,t}$	State of operation, node n, ESS e, time t
$\boldsymbol{\mu}_n/\boldsymbol{\pi}_n$	Pricing dual variables for the Dantzig-Wolfe decomposition, node n
$\Omega^{s^{ty}}_{n,a,t}$	Allocation of power for frequency response service s (ffr/pfr/sfr), type ty (upward/-downward), node n, area a, time t [MW]
$\nu_{n,g,t}$	Binary variable for power-on status (on/off), node n, generator/cluster g, time t

3.1. Problem statement

Uncertainty analysis and stochastic optimisation methods have gained ground in power system planning, becoming an important research area in this field. In particular, to address different long-term uncertainties, models that include multiple scenarios are used to deal with stochastic parameters in power system expansion planning tasks [10]. The multiple-scenario approach seeks to generate a set of possible realisations of random variables in the planning horizon under analysis.

To understand the increasing impact of active demand-side participation on power systems, where uncertainties surround the available capacity, timing, and location of these services, the proposed planning model includes active operational constraints for DER services. Unlike traditional assets, the deployment and availability of DER relies not only on the system operator but also on consumer willingness and their coordination with aggregators and distribution systems. Therefore, a long-term stochastic planning model that considers various future scenarios is crucial to correctly assess the real impact of these services in potentially changing investment portfolios under different unfolding futures.

The proposed model addresses the problem by adopting a multi-stage approach. It organises a total of SC scenarios in a decision tree to represent uncertain parameters such as load growth, VRE and DER deployment, retirement of coal units, and investment and operation costs. Each scenario corresponds to a path from the tree's root to a leaf. In each stage and node n, investment ($\mathbf{X}_n^{\text{inv}}$) and operational ($\mathbf{X}_n^{\text{op}}$) decisions are made, allowing for the optimisation of deploying new infrastructure across different unfolding futures. This mathematical framework maps to the scenario tree, allowing the selection of optimal investment portfolios for each stage depending on the unfolding scenario and guiding the system's expansion in a dynamic, adaptive and informed manner. Figure 3.1 exemplifies the decision tree approach, which contains $|\mathcal{N}|$ nodes and SC scenarios, where investment decisions ($\mathbf{X}_n^{\text{inv}}$) are communicated between nodes to ensure feasible infrastructure development paths.

3.2. Modelling assumptions

The problem formulation is mainly influenced by the experience of the Australian power system (NEM), which forecasts a growing active participation of the demand side. This participation is essential for the system's future development since distributed resources represent a key component in the long-term forecasts of storage capacity, generation and demand response for the next thirty years [7], directly influencing network expansion decisions.

The proposed model assumes that the capacities of distributed storage, distributed generation, and demand response are made available and increase as the planning horizon progresses, following the trajectories associated with each scenario modelled in the problem's scenario tree. For example, the total distributed storage capacity in a specific epoch (year) is not a decision variable

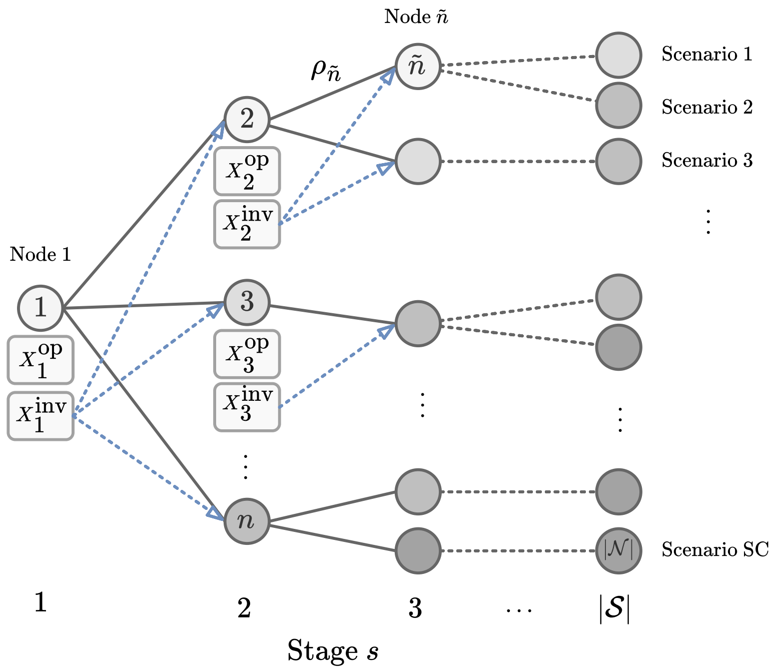


Figure 3.1: Generic formulation and modelling of the decision tree approach as a decision-making architecture.

of the model but rather an input parameter, subject to the conditions modelled in each node of the tree. However, even though the total available capacity is not a decision variable, the operation of the asset is. In this way, the model decides *how* to use the available capacity of each distributed and controllable asset in the system. Also, it is important to note that since the model is used for large-scale system planning, it is assumed that distributed energy resources (i.e. storage, demand response, etc.) are managed and made visible to the system operator through aggregators, following the framework setting explained previously in section 2.1.1.

Several representative weeks are included at each node of the scenario tree to represent the system's operation as accurately as possible. These weeks are selected to capture the system's behaviour hourly throughout different times of the year, incorporating the seasonal variability related to various factors such as load and VRE. By including this level of detail, the model can adequately value and effectively simulate the operation of diverse technologies, including storage, demand response, and synchronous generators with on/off and ramp constraints.

It is worth mentioning that the model presented in this section has been designed from the perspective of the system planner. Thus, all the decisions seek to minimise the total expected costs over the planning horizon, divided into investment and operational costs. In addition, given that the model is directly associated with the scenario tree that represents the future deployment, operational decisions are made at each node of the tree, seeking to determine the most optimal possible operation of the system. It takes into account the infrastructure available up to the corresponding epoch, considering the infrastructure construction decisions made in the previous nodes.

3.3. The multi-stage stochastic expansion planning model

This section describes the main components of the mathematical model that describe the expansion planning problem under uncertainty.

3.3.1. Model overview

The multi-stage stochastic capacity expansion planning model presented in this chapter is a MILP, which extends from [8, 56], and aims to determine the optimal set of transmission and storage investments by minimising the expected total system costs across all the scenarios and time horizon under analysis. The modelling also considers the inclusion of long-term uncertainties in load growth, generation fleet, DER deployment, and fuel and investment costs, which are represented through a multi-stage scenario tree with nodes $n \in \mathcal{N}$.

The expected total system cost comprises the investment and operational costs, weighted by the probability of occurrence of each scenario. In particular, the first stage investment decisions are a crucial insight for the system planner because they correspond to the assets that should be built in the present for the optimal operation of the system in the future. Subsequently, the decisions made in the following nodes reveal the construction of assets required under the different modelled futures.

The candidate assets in the model are transmission lines and utility-scale energy storage (BESS). Given the delay associated with the construction of transmission infrastructure, the model considers the lead time associated with its deployment, limiting the asset's capacity to use. That is, the asset can only be used once the defined lead time has elapsed since the decision to build it was made. Conversely, storage is assumed to be available right after the decision is made within a node, given its faster construction times, providing more adaptability to the system planner. This allows taking decisions after the uncertainties are revealed. The proposed model also allows decisions for investing in DER. However, given that the parameterisation of investment costs of aggregated DER is still under deep discussion in the literature [57], the further case study applications do not consider investments in DER.

Regarding the representation of the operation, the model incorporates highly detailed constraints for different technologies within an hourly resolution and a time-sequential setting to capture the benefits of different flexible technologies. This includes the unit commitment (UC) constraints: minimum stable generation limits, ramp rates, and startup and shutdown times. The operation also considers storage in the form of batteries (BESS), pumped storage (PS) and virtual power plants (VPP). Demand-side services include load shifting (up and down), load reduction, and load shedding. These include the payback effect [58], where overall, the total energy consumption results higher when a load is shifted.

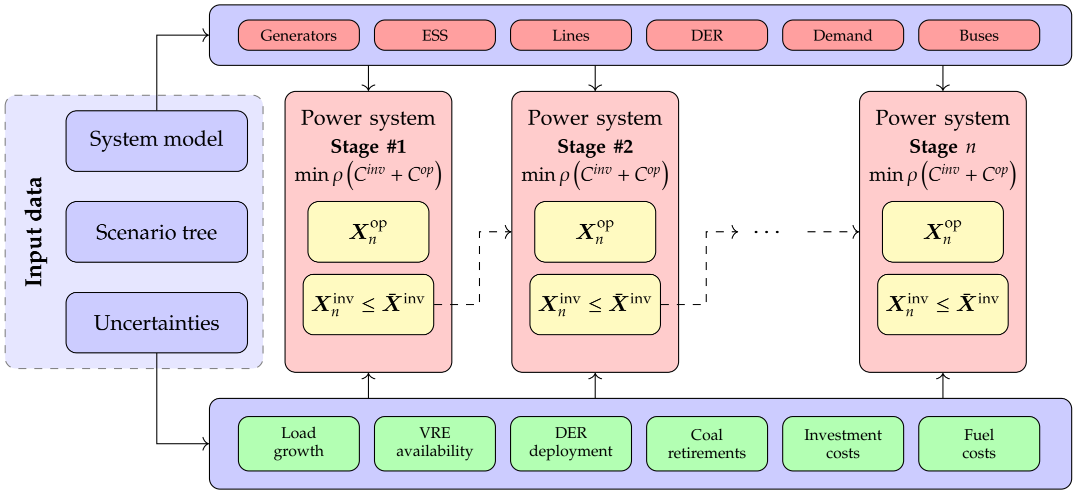


Figure 3.2: General summary of the proposed multi-stage stochastic planning model for a scenario tree with nodes $n \in \mathcal{N}$.

Figure 3.2 summarises the proposed framework and the interactions between input data and operational $\left(\boldsymbol{X}_n^{\mathrm{op}}\right)$ and investment $\left(\boldsymbol{X}_n^{\mathrm{inv}}\right)$ decisions made at each corresponding stage and node n of the scenario tree. It is important to highlight that a stage can be comprised by one or more nodes in the scenario tree.

3.3.2. Objective function

The objective function shown in (3.1), minimises the system's total expected investment and operational costs for all the nodes n of the multi-stage scenario tree. Given the stochastic nature of the model, each node is weighted by its probability of occurrence ρ_n. The costs are further discounted for each node n using a discount rate r to the reference year. The time span between each node and the reference year is measured by y_n

$$\min_{\boldsymbol{X}_n^{\mathrm{inv}}, \boldsymbol{X}_n^{\mathrm{op}}} \sum_{n \in \mathcal{N}} \frac{\rho_n}{(1+r)^{y_n}} \left(C_n^{\mathrm{inv}}\left(\boldsymbol{X}_n^{\mathrm{inv}}\right) + C_n^{\mathrm{op}}\left(\boldsymbol{X}_n^{\mathrm{op}}\right) \right) \tag{3.1}$$

The investment cost (3.2) considers the annualised costs of investing in each transmission, battery storage (BESS) and DER expansion candidates. Once the decision to build an asset is made, the value of the annuity for the corresponding element is paid in each node of the scenario tree.

$$C_n^{\mathrm{inv}}(\boldsymbol{X}_n^{\mathrm{inv}}) = \sum_{l \in \mathcal{L}^{\mathrm{c}}} \pi_{n,l}^{\mathrm{L}} z_{n,l}^{\mathrm{L}} + \sum_{e \in \mathcal{E}^{\mathrm{c}}} \pi_{n,e}^{\mathrm{E}} z_{n,e}^{\mathrm{E}} + \sum_{d \in \mathcal{D}^{\mathrm{c}}} \pi_{n,d}^{\mathrm{D}} z_{n,d}^{\mathrm{D}} \tag{3.2}$$

The operation of the system gives operational costs (3.3) under a set of representative weeks $\mathcal{W}_n$ for each node n of the scenario tree, representing every epoch (year) modelled in the problem. The operation in each representative period is multiplied by a factor $\omega_{n,w}$ to reflect the weight of that representative period in the operation of the year associated with node n. Operational costs include the fuel costs of synchronous units, startup and shutdown, and the cost of DER services:

load shifting and load reduction. The value of load shedding in every bus is priced with the VoLL.

$$C_n^{\mathrm{op}}(\boldsymbol{X}_n^{\mathrm{op}}) = \sum_{b\in\mathcal{B}} \sum_{w\in\mathcal{W}_n} \sum_{t\in\mathcal{T}_w} \omega_{n,w} \cdot \Big(\sum_{g\in\mathcal{G}_b} \Big(c_{n,g}^{\mathrm{fuel}} p_{n,g,t} + c_g^{\mathrm{sup}} \delta_{n,g,t}^{\mathrm{sup}} + c_g^{\mathrm{sdn}} \delta_{n,g,t}^{\mathrm{sdn}} \Big) + \sum_{d\in\mathcal{D}_b} \Big(c_d^{\mathrm{shup}} \gamma_{n,d,t}^{\mathrm{shup}} + c_d^{\mathrm{shdn}} \gamma_{n,d,t}^{\mathrm{shdn}} + c_d^{\mathrm{rd}} \gamma_{n,d,t}^{\mathrm{rd}} \Big) + \mathrm{VoLL} \cdot LS_{n,b,t} \Big) \quad (3.3)$$

3.3.3. Investment constraints

To model the investment in new infrastructure across the nodes of the scenario tree, non-anticipativity constraints [46] are employed. These constraints, (3.4)-(3.6) relate the investments made in the predecessors of node n with the total installed units in that node. This ensures that each investment is available in the subsequent nodes while also imposing limitations on the number of installed units per epoch through the upper bound $\bar{z}_{n,i}^{\mathrm{I}}$ for each asset i in node n.

Additionally, candidate technologies with lead times, particularly transmission lines, cannot be deployed in the root node of the scenario tree, as shown in (3.7). New batteries (BESS) are assumed to become available without any lead time within the same epoch when investment decisions are made.

Investment decisions are represented through non-negative integer variables, as depicted in (3.14). In particular, transmission investment variables are binary because the model is utilised with real investment projects, as imposed in (3.15). Additionally, the investment options can comprise mutually exclusive and must-follow projects. In mutually exclusive sets, only one option is chosen if it minimises overall expected costs. Must-follow projects are those that must be in place for building other options. Simultaneous construction of lines is also permitted.

For the completeness and consistency of the model, equations (3.8)-(3.10) impose the limits for the capacity of the existing assets in the system in each node n of the scenario tree. Moreover, in this case, the existing assets in the system cannot be expanded. This is modelled through equations (3.11)-(3.13)

$$z_{n,l}^{\mathrm{L}} \le \sum_{m\in\mathcal{P}_n} x_{m,l}^{\mathrm{L}} \le \bar{z}_{n,l}^{\mathrm{L}} \qquad \forall n \in \mathcal{N}, l \in \mathcal{L}^{\mathrm{c}} \quad (3.4)$$

$$z_{n,e}^{\mathrm{E}} \le \sum_{m\in\mathcal{P}_n} x_{m,e}^{\mathrm{E}} \le \bar{z}_{n,e}^{\mathrm{E}} \qquad \forall n \in \mathcal{N}, e \in \mathcal{E}^{\mathrm{c}} \quad (3.5)$$

$$z_{n,d}^{\mathrm{D}} \le \sum_{m\in\mathcal{P}_n} x_{m,d}^{\mathrm{D}} \le \bar{z}_{n,d}^{\mathrm{D}} \qquad \forall n \in \mathcal{N}, d \in \mathcal{D}^{\mathrm{c}} \quad (3.6)$$

$$z_{1,l}^{\mathrm{L}} = 0 \qquad \forall l \in \mathcal{L}^{\mathrm{c}} \quad (3.7)$$

$$z_{n,l}^{\mathrm{L}} = \bar{z}_{n,l}^{\mathrm{L}} \qquad \forall n \in \mathcal{N}, l \in \mathcal{L}^{0} \quad (3.8)$$

$$z_{n,e}^{\mathrm{E}} = \bar{z}_{n,e}^{\mathrm{E}} \qquad \forall n \in \mathcal{N}, e \in \mathcal{E}^{0} \quad (3.9)$$

$$z_{n,d}^{\mathrm{D}} = \bar{z}_{n,d}^{\mathrm{D}} \qquad \forall n \in \mathcal{N}, d \in \mathcal{D}^{0} \quad (3.10)$$

$$x^{\mathrm{L}}_{n,l} = 0 \qquad \forall n \in \mathcal{N}, l \in \mathcal{L}^{0} \quad (3.11)$$

$$x^{\mathrm{E}}_{n,e} = 0 \qquad \forall n \in \mathcal{N}, e \in \mathcal{E}^{0} \quad (3.12)$$

$$x^{\mathrm{D}}_{n,d} = 0 \qquad \forall n \in \mathcal{N}, d \in \mathcal{D}^{0} \quad (3.13)$$

$$x^{\mathrm{L}}_{n,l}, x^{\mathrm{E}}_{n,e}, x^{\mathrm{D}}_{n,d} \in \mathbb{Z} \qquad \forall n \in \mathcal{N}, l \in \mathcal{L}^{\mathrm{c}}, e \in \mathcal{E}^{\mathrm{c}}, d \in \mathcal{D}^{\mathrm{c}} \quad (3.14)$$

$$x^{\mathrm{L}}_{n,l} \in \{0, 1\} \qquad \forall n \in \mathcal{N}, l \in \mathcal{L}^{\mathrm{c}} \quad (3.15)$$

3.3.4. Balance equation

Equation (3.16) ensures the produced and withdrawn power is balanced with the demand in every bus b at every hour t, for each representative period w and node n. The dispatches from conventional and renewable generation, the power flows through the lines, and the energy exchanges of storage (ESS) ensure meeting the energy requirements of the demand side at each bus b. The demand side comprises inflexible demand $D_{n,b,w,t}$ and DER. In particular, the term $\kappa_{n,d,t}$ models the power exchanges of every non-controllable and controllable DER. These are controlled through the available flexibility services they can provide through aggregators.

$$\sum_{g \in \mathcal{G}_b \cup \mathcal{R}_b} p_{n,g,t} + \sum_{l \in \mathcal{L}^{\mathrm{to}}_b} f_{n,l,t} - \sum_{l \in \mathcal{L}^{\mathrm{from}}_b} f_{n,l,t} + \sum_{e \in \mathcal{E}_b} \left(p^{\mathrm{dch}}_{n,e,t} - p^{\mathrm{ch}}_{n,e,t} \right) = D_{n,b,w,t} + \sum_{d \in \mathcal{D}_b} \kappa_{n,d,t} - LS_{n,b,t}$$

$$\forall b \in \mathcal{B}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.16)$$

3.3.5. Generation limits and reserves

The model for conventional generators is given by a clustered unit commitment [59]. This consists of grouping units with similar technical properties to use integer variables instead of binary to reduce the complexity of the optimisation problem. In particular, variable $n_{n,g,t}$ measures the number of units turned on for each cluster g.

Each synchronous unit (or cluster of units) is modelled through the set of equations (3.17)-(3.21). These units can provide primary and secondary frequency response (PFR and SFR) during high- and low-frequency events. Downward reserves and minimum stable generation limits are described by (3.17). Upward reserves and maximum outputs are described by (3.18)-(3.21), where the headroom and the operation point determine the limit for the allocation of reserves. In particular, equation (3.19) models the availability of generators through the forced outage rate [60]. This considers the full $\left(\mathscr{F}_g\right)$ and partial $\left(\mathscr{P}_g\right)$ outage rates, limiting the corresponding power output of each unit.

$$n_{n,g,t}\underline{P}_g \leq p_{n,g,t} - p^{\text{pfr}^-}_{n,g,t} - p^{\text{sfr}^-}_{n,g,t} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.17)$$

$$p_{n,g,t} + \frac{p^{\text{pfr}^+}_{n,g,t}}{\text{RS}_g} + p^{\text{sfr}^+}_{n,g,t} \leq n_{n,g,t}\bar{P}_g \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.18)$$

$$p_{n,g,t} \leq n_{n,g,t}\bar{P}_g \left(1 - \left(\mathscr{F}_g + \mathscr{P}_g(1-\alpha_g)\right)\right) \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.19)$$

$$p^{\text{pfr}^+}_{n,g,t} \leq n_{n,g,t}\bar{P}^{\text{pfr}^+}_g \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.20)$$

$$p^{\text{sfr}^+}_{n,g,t} \leq n_{n,g,t}\bar{P}^{\text{sfr}^+}_g \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.21)$$

3.3.6. Unit commitment (UC) constraints

The unit commitment constraints model the scheduling and commitment of power generation units, ramp limitations, startup, shutdown and minimum on-off times. The constraints for synchronous units are given by (3.22)-(3.28), as presented in [59, 61]. The number of online units in each period and the startup-shutdown transitions are described by (3.22). The minimum up-times $\left(\text{T}^{\text{up}}_g\right)$ and down-times $\left(\text{T}^{\text{dn}}_g\right)$ are modelled through (3.23) and (3.24) respectively.

Equation (3.24) integrates the transition times it takes the units to start up $\left(\text{T}^{\text{sup}}_g\right)$ and shutdown $\left(\text{T}^{\text{sdn}}_g\right)$. Each cluster of units will change its output between successive periods limited to the unit's ramping ability and the units that might become active and inactive in the interval. Equation (3.25) represents the upward change in output for a given cluster g, which considers the ramping capability of units and the units that become active in that period. Constraint (3.26) describes the maximum downward change in output for the cluster based on the units' ramping and shutdowns.

Finally, constraint (3.27) ensures the units turned on for each cluster g do not surpass the maximum available units N_g, while constraint (3.28) limits the number of units that can be committed, relative to the number of total available units for each online cluster g. To limit the computational burden associated with the MILP, the integer variables $n_{n,g,t}$, $\nu_{n,g,t}$, $\delta^{\text{sup}}_{n,g,t}$ and $\delta^{\text{sdn}}_{n,g,t}$ can be relaxed for large clusters without introducing substantial errors [59].

$$n_{n,g,t} - n_{n,g,t-1} = \delta^{\text{sup}}_{n,g,t} - \delta^{\text{sdn}}_{n,g,t} \qquad \forall g \in \mathcal{G}, t > 1, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.22)$$

$$n_{n,g,t} \geq \sum_{\tau=t-\text{T}^{\text{up}}_g}^{t} \delta^{\text{sup}}_{n,g,\tau} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.23)$$

$$n_{n,g,t} \leq \text{N}_g - \sum_{\tau=t-\text{T}^{\text{sdn}}_g-\text{T}^{\text{sup}}_g-\text{T}^{\text{dn}}_g}^{t} \delta^{\text{sdn}}_{n,g,\tau} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.24)$$

$$p_{n,g,t} - p_{n,g,t-1} \leq n_{n,g,t-1} \cdot \text{R}^{\text{up}}_g + \delta^{\text{sup}}_{n,g,t} \cdot \underline{P}_g \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.25)$$

$$p_{n,g,t-1} - p_{n,g,t} \leq n_{n,g,t-1} \cdot \text{R}^{\text{down}}_g + \delta^{\text{sdn}}_{n,g,t} \cdot \underline{P}_g \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.26)$$

$$\delta^{\text{sup}}_{n,g,t} - \delta^{\text{sdn}}_{n,g,t} \leq \text{N}_g \cdot \nu_{n,g,t} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.27)$$

$$n_{n,g,t} \leq \text{N}_g \cdot \nu_{n,g,t} \qquad \forall g \in \mathcal{G}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.28)$$

3.3.7. Renewable generation injections

The balance for each renewable generator is presented in (3.29). This equation ensures the available renewable resource at time t, $\tilde{P}^{\mathrm{R}}_{n,g,t}$, is balanced between the power injections $p_{n,g,t}$ and the curtailed power, represented by the variable $p^{\mathrm{cu}}_{n,g,t}$.

$$p_{n,g,t} + p^{\mathrm{cu}}_{n,g,t} = \tilde{P}^{\mathrm{R}}_{n,g,t} \qquad \forall g \in \mathcal{R}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.29)$$

3.3.8. Hydro generators constraints

The maximum generation limits for run-of-river units $\left(\mathcal{G}^{\mathrm{H}}\right)$ are imposed through equation (3.30). The generation limits change depending on the historical inflow data, given by $\xi_{g,w}$ for each generator g and representative period w. On the other hand, the amount of energy that hydro reservoirs $\left(\mathcal{G}^{\mathrm{R}}\right)$ can provide to the system across a representative period w is limited by equation (3.31).

$$p_{n,g,t} \leq \bar{P}_g \cdot n_{n,g,t} \cdot \xi_{g,w} \qquad \forall g \in \mathcal{G}^{\mathrm{H}}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.30)$$

$$\sum_{t \in \mathcal{T}_\omega} p_{n,g,t} \leq \mathrm{NT} \cdot \bar{P}_g \cdot n_{n,g,t} \cdot \xi_{g,w} \qquad \forall g \in \mathcal{G}^{\mathrm{R}}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.31)$$

3.3.9. Transmission constraints

Transmission lines are included in the model following a transportation approach. The forward and reverse maximum capacity of lines are modelled as presented in (3.32). To define the transmission headroom in each direction, equations (3.33)-(3.34) use slack variables $f^{\mathrm{p}}_{n,l,t}$, $f^{\mathrm{n}}_{n,l,t}$.

$$-\underline{F}_{l,t} z^{\mathrm{L}}_{n,l} \leq f_{n,l,t} \leq \bar{F}_{l,t} z^{\mathrm{L}}_{n,l} \qquad \forall l \in \mathcal{L}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.32)$$

$$f_{n,l,t} + f^{\mathrm{p}}_{n,l,t} = \bar{F}_{l,t} z^{\mathrm{L}}_{n,l} \qquad \forall l \in \mathcal{L}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.33)$$

$$f_{n,l,t} + f^{\mathrm{n}}_{n,l,t} = -\underline{F}_{l,t} z^{\mathrm{L}}_{n,l} \qquad \forall l \in \mathcal{L}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.34)$$

3.3.10. Storage constraints

The operation of energy storage systems (ESS) is modelled in equations (3.35)-(3.46). Integer variable $\mu_{n,e,t}$ is employed to determine if the ESS e is in charging ($\mu_{n,e,t} = 0$) or discharging mode ($\mu_{n,e,t} = 1$). Variables $p^{\mathrm{dch}}_{n,e,t}, p^{\mathrm{ch}}_{n,e,t}$ define the power injection or consumption, as presented in (3.35) and (3.36), while (3.37) and (3.38) limit the charging and discharging power depending on the available maximum capacity for each unit.

The upward and downward reserves for frequency response services are respectively modelled through (3.40) and (3.41). The maximum level of FFR is also set through (3.42) for each ESS. The modelling enables the possibility of providing reserves in both directions, either charging or discharging. The energy balance of the ESS is described in (3.43) and (3.44). Equations (3.45) and

(3.46) guarantee the storage has the capacity to provide frequency response (primary or secondary) during the time required for each service.

$$p^{\mathrm{ch}}_{n,e,t} \leq \left(1 - \mu_{n,e,t}\right) \cdot \bar{P}^{\mathrm{ch}}_{e} \qquad \forall e \in \mathcal{E}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.35)$$

$$p^{\mathrm{dch}}_{n,e,t} \leq \mu_{n,e,t} \cdot \bar{P}^{\mathrm{dch}}_{e} \qquad \forall e \in \mathcal{E}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.36)$$

$$p^{\mathrm{ch}}_{n,e,t} \leq \bar{P}^{\mathrm{ch}}_{e} z^{\mathrm{E}}_{n,e} \qquad \forall e \in \mathcal{E}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.37)$$

$$p^{\mathrm{dch}}_{n,e,t} \leq \bar{P}^{\mathrm{dch}}_{e} z^{\mathrm{E}}_{n,e} \qquad \forall e \in \mathcal{E}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.38)$$

$$\mu_{n,e,t} \leq z^{\mathrm{E}}_{n,e} \qquad \forall e \in \mathcal{E}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.39)$$

$$p^{\mathrm{ffr}^+}_{n,e,t} + p^{\mathrm{sfr}^+}_{n,e,t} \leq \mu_{n,e,t} \bar{P}^{\mathrm{dch}}_{e} - p^{\mathrm{dch}}_{n,e,t} + p^{\mathrm{ch}}_{n,e,t} \qquad \forall e \in \mathcal{E}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.40)$$

$$p^{\mathrm{ffr}^-}_{n,e,t} + p^{\mathrm{sfr}^-}_{n,e,t} \leq \left(1 - \mu_{n,e,t}\right) \bar{P}^{\mathrm{ch}}_{e} + p^{\mathrm{dch}}_{n,e,t} - p^{\mathrm{ch}}_{n,e,t} \qquad \forall e \in \mathcal{E}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.41)$$

$$p^{\mathrm{ffr}^-}_{n,e,t}, p^{\mathrm{ffr}^+}_{n,e,t} \leq \bar{P}^{\mathrm{ffr}}_{e} \qquad \forall e \in \mathcal{E}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.42)$$

$$e^{\mathrm{E}}_{n,e,t} = \eta^{\mathrm{ch}}_{e} p^{\mathrm{ch}}_{n,e,t} - \frac{p^{\mathrm{dch}}_{n,e,t}}{\eta^{\mathrm{dch}}_{e}} + e^{\mathrm{E}}_{n,e,t-1} \qquad \forall e \in \mathcal{E}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.43)$$

$$\underline{E}_{e} z^{\mathrm{E}}_{n,e} \leq e^{\mathrm{E}}_{n,e,t} \leq \bar{E}_{e} z^{\mathrm{E}}_{n,e} \qquad \forall e \in \mathcal{E}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.44)$$

$$p^{\mathrm{ffr}^+}_{n,e,t} \mathrm{T}^{\mathrm{pfr}} + p^{\mathrm{sfr}^+}_{n,e,t} \mathrm{T}^{\mathrm{sfr}} \leq e^{\mathrm{E}}_{n,e,t} - \underline{E}_{e} \qquad \forall e \in \mathcal{E}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.45)$$

$$p^{\mathrm{ffr}^-}_{n,e,t} \mathrm{T}^{\mathrm{pfr}} + p^{\mathrm{sfr}^-}_{n,e,t} \mathrm{T}^{\mathrm{sfr}} \leq \bar{E}_{e} - e^{\mathrm{E}}_{n,e,t} \qquad \forall e \in \mathcal{E}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.46)$$

This model is applicable for different types of storage, namely batteries (BESS) and pumped-hydro storage (PS), and also for virtual power plants (VPP). The difference is that BESS are capable of providing fast frequency response (FFR) through $p^{\mathrm{ffr}^-}_{n,e,t}, p^{\mathrm{ffr}^+}_{n,e,t}$ in (3.40)-(3.42), (3.45) and (3.46), whereas PS participates in PFR instead of FFR by replacing the FFR variables of the previous equations with $p^{\mathrm{pfr}^-}_{n,e,t}, p^{\mathrm{pfr}^+}_{n,e,t}$, also providing inertia to the system.

3.3.11. Allocation of system reserves

This section describes the expressions associated with the aggregated reserves per area in the system. This allows the formulation of the systems' security constraints. Equations (3.47)-(3.49) describe the total allocation of power for FFR, PFR, and SFR services of type ty in each area a, respectively.

$$\Omega^{\mathrm{ffr}^{ty}}_{n,a,t} = \sum_{e \in \mathcal{E}_a} p^{\mathrm{ffr}^{ty}}_{n,e,t} \qquad \forall a \in \mathcal{A}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N}, \forall ty \quad (3.47)$$

$$\Omega^{\mathrm{pfr}^{ty}}_{n,a,t} = \sum_{g \in \mathcal{G}_a} p^{\mathrm{pfr}^{ty}}_{n,g,t} + \sum_{e \in \mathcal{E}_a} p^{\mathrm{pfr}^{ty}}_{n,e,t} \qquad \forall a \in \mathcal{A}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N}, \forall ty \quad (3.48)$$

$$\Omega^{\mathrm{sfr}^{ty}}_{n,a,t} = \sum_{g \in \mathcal{G}_a} p^{\mathrm{sfr}^{ty}}_{n,g,t} + \sum_{e \in \mathcal{E}_a} p^{\mathrm{sfr}^{ty}}_{n,e,t} \qquad \forall a \in \mathcal{A}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N}, \forall ty \quad (3.49)$$

The determination of contingencies for both load and generation is conducted for each area a rather than for the whole system. This allows defining the allocation of reserves in a more granular fashion. Equation (3.50) allows defining the largest loss of generation in each area a, while (3.51) determines the largest load contingency for each area and period. This value must be determined as an input parameter for the problem since the unit commitment model does not consider the demand dispatch.

$$\Delta p^{gen-\text{loss}}_{n,a,t} \geq p_{n,g,t} \qquad \forall g \in \mathcal{G}_a, a \in \mathcal{A}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.50)$$

$$\Delta p^{load-\text{loss}}_{n,a,t} \geq \text{LL}_{n,a,t} \qquad \forall a \in \mathcal{A}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.51)$$

Equations (3.52)-(3.53) model the quasi steady state frequency (QSSF) constraints. These constraints ensure enough local FFR and PFR reserves in each area of the system are available to comply with the QSSF for losses of load or generation.

$$\Omega^{\text{ffr}^+}_{n,a,t} + \Omega^{\text{pfr}^+}_{n,a,t} \geq \Delta p^{gen-\text{loss}}_{n,a,t} + \sigma_a \Delta f^{qssf^-} \cdot \textstyle\sum_{b\in\mathcal{B}_a} D_{n,w,b,t} \qquad \forall a \in \mathcal{A}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.52)$$

$$\Omega^{\text{ffr}^-}_{n,a,t} + \Omega^{\text{pfr}^-}_{n,a,t} \geq \Delta p^{load-\text{loss}}_{n,a,t} - \sigma_a \Delta f^{qssf^+} \left(\textstyle\sum_{b\in\mathcal{B}_a} D_{n,w,b,t} - \Delta p^{load-\text{loss}}_{n,a,t}\right) \qquad \forall a \in \mathcal{A}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.53)$$

Similarly, secondary frequency response reserves (SFR) are allocated through equations (3.54)-(3.55) for each area and event type, aiming to bring the frequency back to the dead band.

$$\Omega^{\text{sfr}^+}_{n,a,t} \geq \Delta p^{gen-\text{loss}}_{n,a,t} - \sigma_a \left|\Delta f^{db}\right| \sum_{b\in\mathcal{B}_a} D_{n,w,b,t} \qquad \forall a \in \mathcal{A}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.54)$$

$$\Omega^{\text{sfr}^-}_{n,a,t} \geq \Delta p^{load-\text{loss}}_{n,a,t} - \sigma_a \left|\Delta f^{db}\right| \left(\sum_{b\in\mathcal{B}_a} D_{n,w,b,t} - \Delta p^{load-\text{loss}}_{n,a,t}\right) \qquad \forall a \in \mathcal{A}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.55)$$

3.3.12. Distributed energy resources (DER) constraints

In the proposed model, distributed energy resources (DER) are modelled in an aggregated fashion, enabling them to offer local flexibility services via equations (3.56)-(3.61) in each bus of the system. Equation (3.56) captures the hourly power exchanges of each DER, with $\tilde{\kappa}_{n,d,t}$ representing inflexible exchanges (independent of market signals). If a DER is non-controllable, terms related to load shifting ($\gamma^{\text{shup}}_{n,d,t}, \gamma^{\text{shdn}}_{n,d,t}$) and reduction ($\gamma^{\text{red}}_{n,d,t}$) are omitted; otherwise, these terms model the active power exchanges of these services.

Equations (3.57)-(3.59) model load shifting. This service allows for a reduction in energy consumption at a given time and shifts the demand to hours where energy is more economical. This reduces system operational costs while taking advantage of resource fluctuations. Equation (3.59) restricts load rebalancing to occur every T^{rec}_d periods. This service can be customised for each different DER included in the model to accommodate different flexibility types and durations. Furthermore, the parameter ζ_d in equation (3.59) accounts for the payback effect [58], reflecting the interplay between appliance characteristics and their consumption patterns.

$$\kappa_{n,d,t} = \tilde{\kappa}_{n,d,t} + \gamma^{\text{shup}}_{n,d,t} - \gamma^{\text{shdn}}_{n,d,t} - \gamma^{\text{red}}_{n,d,t} \qquad \forall d \in \mathcal{D}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.56)$$

$$e^{\text{shup}}_{n,d,t} = e^{\text{shup}}_{n,d,t-1} + \gamma^{\text{shup}}_{n,d,t} \qquad \forall d \in \mathcal{D}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.57)$$

$$e^{\text{shdn}}_{n,d,t} = e^{\text{shdn}}_{n,d,t-1} + \gamma^{\text{shdn}}_{n,d,t} \qquad \forall d \in \mathcal{D}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.58)$$

$$e^{\text{shup}}_{n,d,t} = (1 + \zeta_d) \cdot e^{\text{shdn}}_{n,d,t} \qquad \forall d \in \mathcal{D}, t \in \mathcal{T}, t \bmod T^{\text{rec}}_d = 0, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.59)$$

$$0 \leq \gamma^{\text{shup}}_{n,d,t} \leq \bar{\gamma}^{\text{shup}}_d z^{\text{D}}_{n,d} \qquad \forall d \in \mathcal{D}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.60)$$

$$0 \leq \gamma^{\text{shdn}}_{n,d,t} \leq \bar{\gamma}^{\text{shdn}}_d z^{\text{D}}_{n,d} \qquad \forall d \in \mathcal{D}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.61)$$

$$0 \leq \gamma^{\text{red}}_{n,d,t} \leq \bar{\gamma}^{\text{red}}_d z^{\text{D}}_{n,d} \qquad \forall d \in \mathcal{D}, t \in \mathcal{T}_w, w \in \mathcal{W}_n, n \in \mathcal{N} \quad (3.62)$$

The proposed framework also integrates load reduction (peak shaving), allowing the modelling of specific devices that reduce their power consumption as a way of demand response. Equations (3.56) and (3.64) model this service, which is penalised in the objective function (3.16) with a cost (as a means of payment to the customer) for energy that is not consumed. Finally, equations (3.60)-(3.62) limit the power exchange capacity for both existing and candidate assets.

Importantly, in the proposed model, each bus can host multiple DER d, allowing independent modelling of different technologies. For example, at bus b, electric vehicles (EVs) can be represented through load shifting, while appliances (e.g. air conditioning or washing machines) can be modelled independently via load reduction.

3.4. Solution strategy

The proposed model poses significant challenges in terms of execution times and memory requirements due to its large-scale mixed-integer linear nature. Even the most advanced commercial solvers encounter limitations when addressing such complexity. Prior research has explored various approaches to address these challenges, with the Dantzig-Wolfe (DW) decomposition emerging as one of the most effective approaches in similar problems [8, 9].

By strategically implementing the DW decomposition and leveraging the block-diagonal structure of the problem, it becomes tractable without the need for oversimplification. The block-diagonal structure allows for a natural division of the problem into independent operational subproblems. This, in turn, enables the DW decomposition to split the whole problem effectively into a single master problem and a set of manageable subproblems.

3.4.1. Problem reformulation

The multi-stage stochastic problem is reformulated to apply the DW decomposition using the approach presented in [46]. In order to do this, the feasible region $\mathcal{Z}_n$ of total installed units in each node n, which includes transmission lines, ESS and DER, is defined in (3.63) as a bounded integer polyhedron. Therefore, any point in $\mathcal{Z}_n$ can be expressed as a combination of a finite number of integer points, $\left\{\hat{Z}_{n,j}\right\}_{j\in\mathcal{K}_n}$ in $\mathcal{Z}_n$ [62], as shown in (3.64)-(3.66) :

$$\mathcal{Z}_n = \{\boldsymbol{Z}_n \in \mathbb{Z}_+^{|\mathcal{L}|+|\mathcal{E}|+|\mathcal{D}|} \mid \exists \boldsymbol{X}_n^{\text{op}} \in \mathcal{X}_n,\ \boldsymbol{A}_n \boldsymbol{X}_n^{\text{op}} \leq \boldsymbol{U}_n \boldsymbol{Z}_n \leq \bar{\boldsymbol{Z}}_n\} \tag{3.63}$$

$$\boldsymbol{Z}_n = \sum_{j \in \mathcal{K}_n} \lambda_{n,j} \hat{\boldsymbol{Z}}_{n,j} \tag{3.64}$$

$$\sum_{j \in \mathcal{K}_n} \lambda_{n,j} = 1 \tag{3.65}$$

$$\lambda_{n,j} \in \{0, 1\} \tag{3.66}$$

For each feasible vector of installed units in node n, $\hat{\boldsymbol{Z}}_{n,j}$, at least one corresponding optimal operational plan $\hat{\boldsymbol{X}}_{n,j}^{\text{op}}$ exists. Therefore, $\boldsymbol{X}_n^{\text{op}}$ can be expressed as a convex combination of the different plans $\hat{\boldsymbol{X}}_{n,j}^{\text{op}}$ obtained:

$$\boldsymbol{X}_n^{\text{op}} = \sum_{j \in \mathcal{K}_n} \lambda_{n,j} \hat{\boldsymbol{X}}_{n,j}^{\text{op}} \tag{3.67}$$

3.4.2. Master problem

The master problem (3.68)-(3.72) of the DW decomposition is reformulated by substituting $\boldsymbol{Z}_n$ and $\boldsymbol{X}_n^{\text{op}}$ in the original compact reformulation of the problem, shown in [62]. Constraints (3.69)-(3.70) ensure the selection of one and only one vector of operation and infrastructure for each node n of the scenario tree. Additionally, the associated dual prices of these constraints are $\boldsymbol{\pi}_n$ and $\boldsymbol{\mu}_n$, which are sent to the corresponding subproblem $(\text{SP})_n$ of each node n in each iteration of the column generation algorithm.

$$\min \quad Z_{RMP}^{IP} = \sum_{n \in \mathcal{N}} \rho_n \left(\boldsymbol{c}_n^{\text{inv}^\top} \boldsymbol{X}_n^{\text{inv}} + \sum_{j \in \mathcal{K}_n} \lambda_{n,j} \boldsymbol{c}_n^{\text{op}^\top} \hat{\boldsymbol{X}}_{n,j} \right) \tag{3.68}$$

$$\text{s.t.:} \quad \sum_{j \in \mathcal{K}_n} \lambda_{n,j} \hat{\boldsymbol{Z}}_{n,j} \leq \sum_{h \in \mathcal{P}_n} \boldsymbol{X}_h^{\text{inv}} \qquad [\boldsymbol{\pi}_n] \qquad \forall n \in \mathcal{N} \tag{3.69}$$

$$\sum_{j \in \mathcal{K}_n} \lambda_{n,j} = 1 \qquad [\boldsymbol{\mu}_n] \qquad \forall n \in \mathcal{N} \tag{3.70}$$

$$\lambda_{n,j} \in \{0, 1\} \qquad \forall n \in \mathcal{N} \tag{3.71}$$

$$\boldsymbol{X}_n^{\text{inv}} \in \mathbb{Z}^+ \qquad \forall n \in \mathcal{N} \tag{3.72}$$

3.4.3. Subproblem

An optimal solution for the master (investment) problem can be found iteratively by applying the Column Generation algorithm [62]. This approach allows obtaining new columns $\left\{\hat{\boldsymbol{Z}}_{n,j}, \hat{\boldsymbol{X}}_{n,j}^{\text{op}}\right\}$ by solving subproblem $(\text{SP})_n$ for each node n of the scenario tree, which minimises the reduced cost of the generated column for each node n of the tree, z_n^{sp}.

$$\text{(SP)}_n \quad z_n^{\text{sp}} = \min \quad \rho_n \boldsymbol{c}_n^{\text{op}^\top} \boldsymbol{X}_n^{\text{op}} - \boldsymbol{\pi}_n^\top \boldsymbol{Z}_n - \boldsymbol{\mu}_n \tag{3.73}$$

$$\text{s.t.:} \quad \boldsymbol{X}_n^{\text{op}} \in \mathcal{X}_n \tag{3.74}$$

$$\boldsymbol{A}_n \boldsymbol{X}_n^{\text{op}} \leq \boldsymbol{U}_n \boldsymbol{Z}_n \leq \bar{\boldsymbol{Z}}_n \tag{3.75}$$

$$\boldsymbol{Z}_n \in \mathbb{Z}_+^{|\mathcal{L}|+|\mathcal{E}|+|\mathcal{D}|} \tag{3.76}$$

3.4.4. Solution algorithm

As explained previously, the Column Generation algorithm is applied to the decomposed problem (via the Dantzig-Wolfe decomposition) to find an optimal investment solution iteratively. Through this approach, if the value of the objective function z_n^{sp} (reduced cost) of the subproblem associated to node n, $(SP)_n$, solved via (3.73) - (3.76) is negative, the introduction of a new column to the master problem (3.68) can eventually reduce the total costs.

Thus, if the condition of having a negative reduced cost is met, the master problem is updated by adding all the columns $\left\{\hat{\boldsymbol{Z}}_{n,j}, \hat{\boldsymbol{X}}_{n,j}^{\text{op}}\right\}$ found in the subproblems with a negative reduced cost. Subsequently, in each iteration, the dual variables $\boldsymbol{\mu}_n$ and $\boldsymbol{\pi}_n$ associated with the master's problem constraints are sent to each subproblem $(SP)_n$ to measure the impact of a generated column in the optimal solution Z_{RMP}^{IP}. Particularly, the total cost of the master problem can be reduced in each iteration until a stopping criterion is reached.

The first criterion for stopping the algorithm corresponds to when it is not possible to generate new columns that can reduce the cost of the restricted master problem (RMP). In that case, the optimum of the linear relaxation of the RMP has been reached, and consequently, the problem is solved with integrality constraints. A second stopping criterion is also imposed. This criterion is evaluated over the LP_{gap} (calculated from the linear relaxation of the master problem) at the current iteration. In case the LP_{gap} meets the desired criterion (given a tolerance), the MIP_{gap} (associated with the master problem with integrality constraints) is subsequently calculated. In case tolerance ranges for both values are met, the algorithm stops, and an optimal solution has been found. Both LP_{gap} and MIP_{gap} are calculated as follows [33]:

$$LB := Z_{RMP}^{LP} \tag{3.77}$$

$$LP_{gap} = \frac{\left(Z_{RMP}^{LP} - LB\right)}{LB}; \quad MIP_{gap} = \frac{\left(Z_{RMP}^{IP} - LB\right)}{LB} \tag{3.78}$$

Algorithm 1 summarises the steps described previously towards the execution and implementation of column generation for solving the optimisation problem presented in Section 3.3.

Algorithm 1: Column generation algorithm

Data: System data, scenario parameters, scenario tree, target gap Δ^{gap}.
Init: $LB = -\infty$, $UB = \infty$, $LP_{gap} = \infty$, $MIP_{gap} = \infty$.
Result: Optimal values for variables of the RMP, $\boldsymbol{X}_n^{\text{inv}}$, $\forall n$.

while $MIP_{gap} > \Delta^{gap}$ **do**
  while $LP_{gap} > \Delta^{gap}$ **do**
    $it = it + 1$;
    Solve the linear relaxation of the RMP (3.68)-(3.72);
    Obtain and store values of the dual variables $\boldsymbol{\pi}_n$, $\boldsymbol{\mu}_n$, $\forall n$;
    for $n \in \mathcal{N}$ **do**
      Solve $(SP)_n$ with dual variables $\boldsymbol{\pi}_n$, $\boldsymbol{\mu}_n$;
      Obtain column $\left\{\hat{\boldsymbol{Z}}_{n,j}, \hat{\boldsymbol{X}}^{\text{op}}_{n,j}\right\}$;
      if $z_n^{sp} < 0$ **then**
        Add column $\left\{\hat{\boldsymbol{Z}}_{n,j}, \hat{\boldsymbol{X}}^{\text{op}}_{n,j}\right\}$ to the RMP
      end
    end
    Calculate $LB = Z^{LP}_{RMP}$;
    Calculate $LP_{gap} = \frac{\left(Z^{LP}_{RMP} - LB\right)}{LB}$;
  end
  Solve RMP (3.68)-(3.72) ;
  Calculate $MIP_{gap} = \frac{\left(Z^{IP}_{RMP} - LB\right)}{LB}$
end

Chapter 4

Case studies

This chapter describes the system model and the scenarios employed in this work's case study applications. Key trends of the scenarios, like the generation and storage fleet, adoption of distributed energy resources, and retirements of coal-fired power plants, are also detailed. Subsequently, the chapter delves into the scenario tree designed for the proposed stochastic model and describes the case study applications.

The data and studies presented in this and the following sections use as their main source the information presented in the 2022 Integrated System Plan (ISP) [7] for the Australian National Electricity Market (NEM). It is important to note that the stochastic model presented in Chapter 3 is a planning methodology that differs from that employed in the ISP to determine the recommendations for the expansion of the transmission network. Nevertheless, it is relevant to describe it to understand the input data for the studies to be carried out.

4.1. System model and input data

4.1.1. The National Electricity Market

The National Electricity Market (NEM) is composed of five main areas, namely, Queensland (QLD), New South Wales (NSW), Victoria (VIC), South Australia (SA) and Tasmania (TAS). As illustrated in Figure 4.1, these regions are further divided into a 10-node sub-regional model corresponding to the one used to develop this work. It is important to remark that the system operator, AEMO, uses the same system model for expansion planning purposes.

The system model under consideration results from the outcomes of the Inputs, Assumptions and Scenarios database associated with the ISP 2022 [63]. Part of the data used for this work was obtained from the results of the optimal development path found in the ISP 2022, which corresponds to candidate development path number 12.

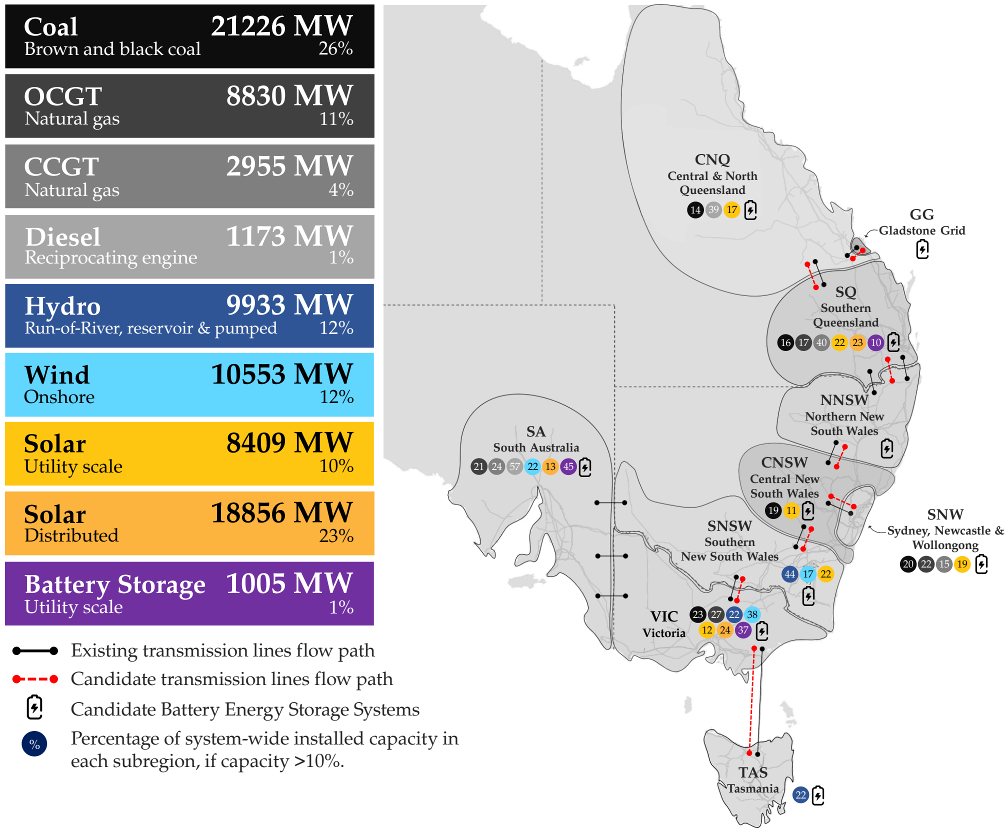
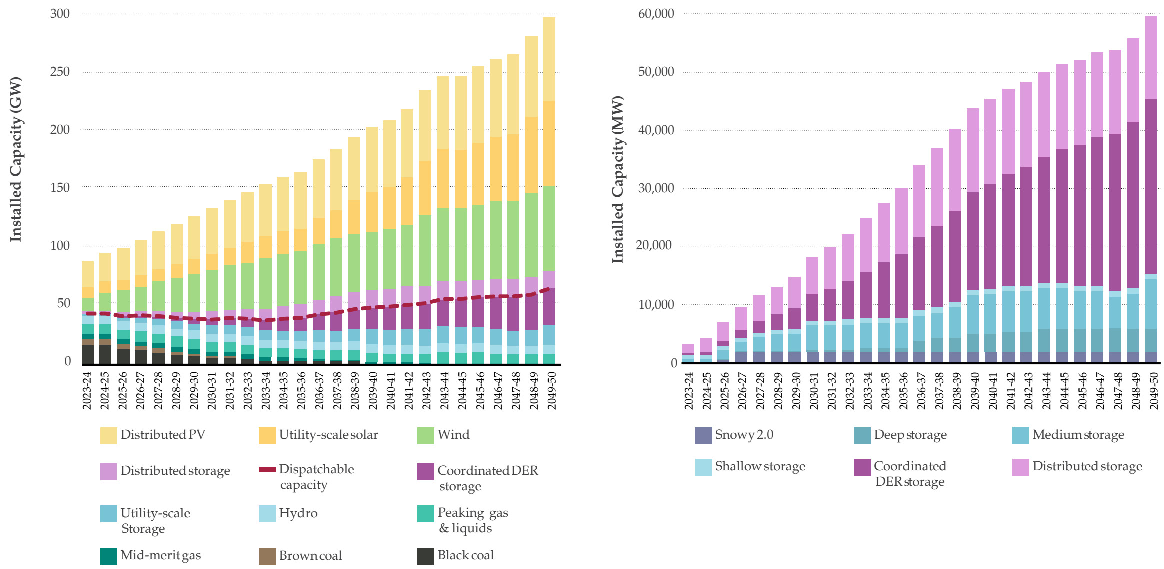


Figure 4.1: Sub-regional system model of the National Electricity Market, Australia.

Figure 4.1 also summarises the total installed capacity in the NEM for each technology for the most probable scenario *(Step Change)* in the 2022 ISP [7]. In addition, Figure 4.2 illustrates the expected development of the installed capacity of each technology in the NEM until 2050 for this scenario. This development path shows significant growth for the installed capacity of renewable technologies such as utility-scale solar and distributed PV, as well as a considerable increase of coordinated distributed storage, which by 2050 represents the largest storage capacity in the system. This poses significant challenges for planning the integration of multiple technologies emerging from different sources, both at large scale and from the consumer side.

4.1.2. 2022 Integrated System Plan and scenarios under consideration

AEMO's Integrated System Plan (ISP) is a comprehensive planning roadmap that covers a 20-year decision horizon. It considers the impact of distributed energy resources, grid-scale generators, energy storage systems, high-voltage transmission and gas systems, hydro resources, and the electrification of transport. The 2022 ISP also considers the impact of Australia's emerging global hydrogen economy and addresses the power system's needs for reliability, security, policy objectives, and system standards. The primary outcomes from this integrated process are the recommendations for the expansion of the transmission infrastructure necessary to leverage the transition from a high-coal generation mix to a low-carbon system dominated by variable renewable energy and



(a) Generation mix.

(b) Storage mix.

Figure 4.2: Projections for the installed capacity of generation and storage in the *Step Change* scenario in the NEM. Extracted from [7].

distributed energy resources (DER), using a least-cost and least-regret approach.

To determine the optimal transition path for the system, the ISP models the future through a set of independent scenarios illustrated in Figure 4.3. These scenarios are characterised by varying load levels, supply (variable renewable energy and DER), energy storage, investment and fuel costs, the behaviour of the gas and electricity markets, and other factors. Figure 4.3 shows how each scenario balances the decentralisation regarding the participation of the consumer side in the generation mix and the underlying operational demand seen by the transmission network in each scenario.

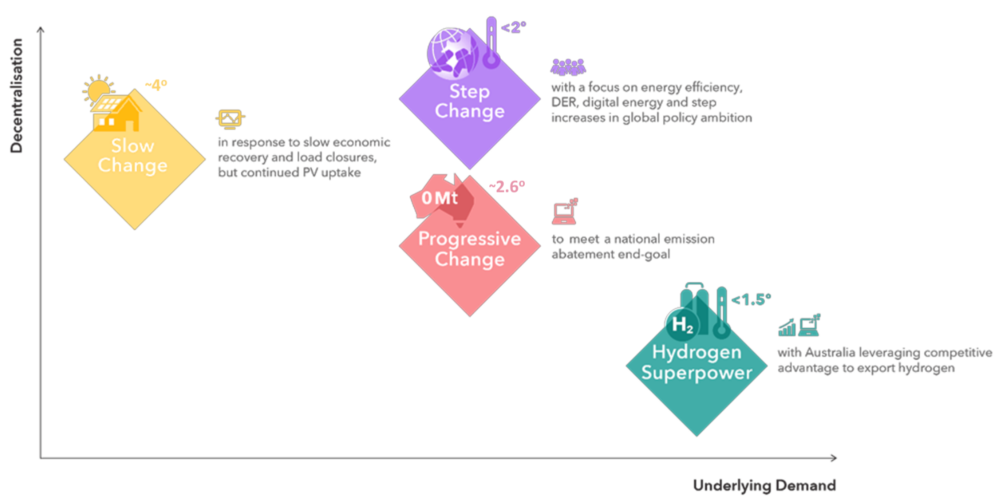


Figure 4.3: Scenarios in the 2022 Integrated System Plan (ISP) for the NEM. Extracted from [7].

Annex A further describes the details and assumptions for each scenario considered in the 2022 ISP [7], which are also modelled in the same way for the development of this work.

4.1.3. Input data

The system under analysis corresponds to the Australian NEM, as shown in Figure 4.1. Part of the input data used in this work was obtained from the results associated with the ODP found in the 2022 ISP [7], which corresponds to the CDP 12 and is detailed in the following sections.

4.1.3.1. System and scenario trends

The system model used for the case studies in this work consists of five main areas, which are then divided into ten subregions, which make up the 10-bus model shown previously in Figure 4.1. The VoLL in the system is 15 000 $\frac{\$}{\mathrm{MWh}}$. The QSSF target for a generator loss is 49.5 Hz, and the load damping factor is 2%. The most significant loss of generation is 744 MW. The bus and area distribution of the system is detailed in Table 4.1.

Table 4.1: Distribution of areas and buses in the system model.

State name	Queensland			New South Wales				Victoria	Tasmania	South Australia
Area	QLD			NSW				VIC	TAS	SA
Buses	CNQ	GG	SQ	NNSW	CNSW	SNW	SNSW	VIC	TAS	SA

The transmission network in the system model considers 11 existing links between the subregions, whose power transfer capacities are detailed in Table 4.2. The list also includes the *Project EnergyConnect*, which is under development but is expected to start operations in 2026. Following the approach from the ISP, Kirchoff's voltage law is not modelled, which is generally not an issue, as the network is mainly radial, except for the loop between SA, NSW and VIC. This approximation might affect the valuation of investment options between NSW and VIC [64].

The system model includes four types of existing storage systems: behind-the-meter storage, coordinated distributed storage, battery storage systems (BESS) and pumped-hydro storage systems (PS) with different charging depths. The effect of behind-the-meter storage is included in the demand profiles. Controllable distributed storage is handled in the form of an aggregator as a virtual power plant (VPP) with dispatchable capacity only to perform arbitrage in the system.

The utility-scale storage is organised into three categories depending on the duration: shallow, medium, and deep. Shallow storage duration is assumed to be less than 4 hours, medium storage covers between 4 and 12 hours, and deep storage considers every unit above 12 hours of storage capacity. For existing and new BESS, the round-trip efficiency is considered 82% and 72% for PS. Table B.1 summarises the existing utility-scale storage units in the system considered for the case study applications of this work. It is important to remark that the optimal dispatchable storage capacity identified by AEMO in their ISP is included in the model as an input parameter.

The existing generation units are grouped into clusters of equivalent generators per technol-

Table 4.2: Parameters of existing and expected transmission lines.

#	Name	Reg. A	Reg. B	Transfer limits [MW]	
				A to B	B to A
1	CNQ - GG	CNQ	GG	1100	1050
2	SQ - CNQ	SQ	CNQ	2100	1000
3	QNI	NNSW	SQ	1170	745
4	Terranora	NNSW	SQ	200	50
5	CNSW - NNSW	CNSW	NNSW	1025	910
6	CNSW - SNW	CNSW	SNW	6125	7625
7	SNSW - CNSW	SNSW	CNSW	2590	2950
8	VNI	VIC	SNSW	400	1000
9	Heywood	VIC	SA	650	650
10	Murraylink	VIC	SA	200	220
11	Basslink	TAS	VIC	478	478
12	Project EnergyConnect	SNSW	SA	800	800

ogy to increase the computational efficiency of the model while maintaining a good operational resolution. Table 4.3 presents the techno-economic parameters of the synchronous units for 2022. Figure 4.4 shows the evolution of coal units' retirements by scenario. The generation clusters that include coal units are modified depending on the specific changes in the generation fleet described in the ODP found in the ISP.

Table 4.3: Techno-economic parameters of existing synchronous generators in the NEM.

Technology	Coal	Hydro	OCGT	CCGT	Diesel
Number of units	48	104	85	19	22
Variable cost [$/MWh]	13-30	7.5	117 - 181	64 - 100	127 - 478
Start-up costs [k$]	27 - 57	–	0.4 - 6.5	12 - 46	–
Rated power [MW]	280 - 744	15 - 144	33 - 219	48 - 385	31 - 114
Forced outage rate [p.u.]	0.76 - 0.86	0.97	0.93 - 0.94	0.95	0.93
MSG [MW]	110 - 330	3 - 29	11 - 72	20 - 190	6 - 22
Ramp rate [MW/min]	4 - 8	–	3 - 7	2 - 11	–
Min up time [h]	8 - 16	–	–	4 - 6	–

Non-synchronous generation is split into large-scale wind, large-scale solar PV, and distributed PV, which are represented as a single unit in each subregion of the system model. The capacity of these units changes in time to reflect the growth of the installed capacity. To access the most accurate information about the demand in the system, distributed PV is modelled as a separate generation unit, hence avoiding the need to subtract it from the demand in each subregion. Reference installed capacity for each technology and scenario is summarised in Figure 4.8.

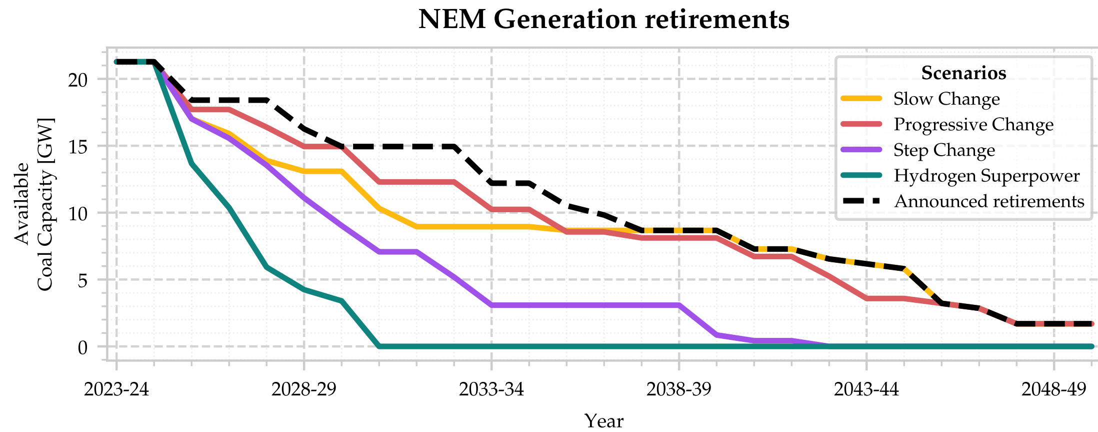


Figure 4.4: Expected retirements of coal-fired power plants in the 2022 ISP.

Beyond the traditional transmission, generation, and storage assets, the studied system incorporates a significant penetration of controllable distributed energy resources (DER) in the medium and long term. Given their projected high participation as dispatchable technologies in the system, these resources are crucial for expansion planning. Notably, controllable distributed storage and demand response capacities are critical inputs, as their flexibility influences investment decisions. Figure 4.5 summarises the state-by-state evolution of these resources over the study period in our case studies.

The presented model is capable of differentiating between controllable and non-controllable DER. Controllable DER actively participates in the market, while non-controllable resources operate "behind the meter" with fixed hourly profiles. Controllable distributed energy storage is modelled through a virtual power plant (VPP) operated by an aggregator, as described in [7]. Demand response enables load shifting with a maximum recovery time of 24 hours T_d^{rec} and a 10% energy consumption payback (ζ_d = 10%), allowing flexible demand management.

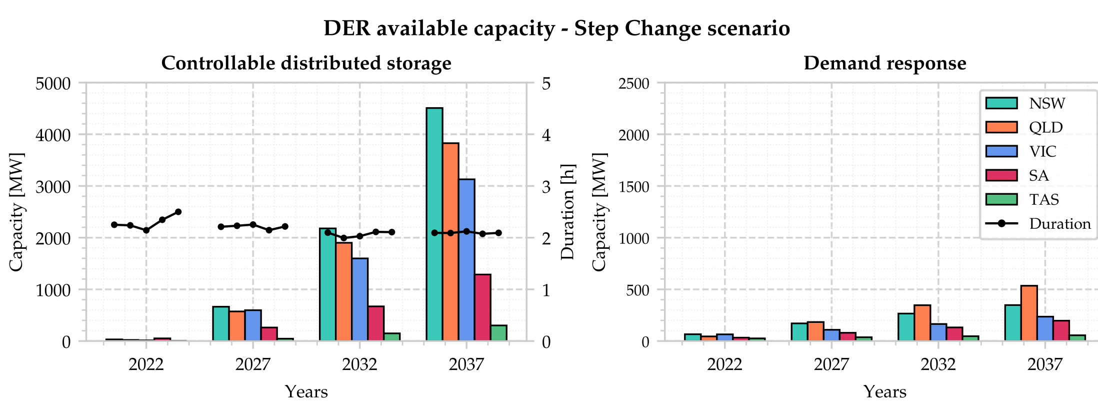


Figure 4.5: Regional disaggregation of maximum available capacities and duration of the studied flexible DER for AEMO's *Step Change* scenario.

4.1.3.2. Investment candidates

Investment options for the case study applications include transmission lines and utility-scale BESS. Investment-related cash flow manipulations (annuities, discounting, etc.) are calculated using a capital cost of 10%, which follows the values employed by AEMO [7].

The proposed model allows for including investments in real transmission options. Thus, the transmission investment candidates are all the projects considered in the 2022 ISP. Additionally, the model provides the option to restrict the investment in specific projects due to the requirement of the existence of another. In this way, the portfolio of candidate options considers *mutually exclusive* and *must-follow* options.

Table 4.4 summarises the parameters for candidates to reinforce the transmission network. Additionally, Annex C provides the details of each candidate project. For the sake of simplicity, all reinforcement options consider a lifetime of 50 years and a lead time of 5 years (the time elapsed between the moment the investment is decided and the moment the asset starts operating). The investment costs presented in Table 4.4 correspond to the overnight capital costs, and it is assumed that these costs do not vary in the future.

Table 4.4: Parameters of candidate transmission lines.

Reg. A	Reg. B	Nº options	Transfer limits [MW] A to B	B to A	Inv. Cost [M$/MW]
CNQ	GG	1	550	500	0.74
SQ	CNQ	3	0 - 1500	300 - 1500	0.18 - 1.08
NNSW	SQ	3	550 - 1800	800 - 2000	0.48 - 1.56
CNSW	NNSW	11	585 - 2750	470 - 2750	0.18 - 2.72
CNSW	SNW	6	600 - 5000	0 - 5000	0.18 - 3.76
SNSW	CNSW	3	2000 - 2200	2000 - 2200	0.48 - 1.51
VIC	SNSW	5	1930 - 2000	1500 - 2000	1.16 - 1.52
TAS	VIC	2	750	750	1.87 - 3.17

The case studies also consider additional investment in energy storage systems (BESS). To maintain the tractability of the case studies and understand the impact of utility-scale storage on investment portfolios, only 4-hour capacity BESS units are considered. This configuration was selected to reflect the value of shallow and medium-depth storage, which are also compared to the duration of distributed storage. Each subregion can expand up to 10 GW in blocks of 50 MW, as shown in the blue points in Figure 4.6.

This means that the model explores candidate multiples of 50 MW batteries with a capacity of 200 MWh. The investment parameters are presented in Table 4.5. To model storage, no lead time is considered, i.e., the decision to build storage and the availability of the device occur simultaneously.

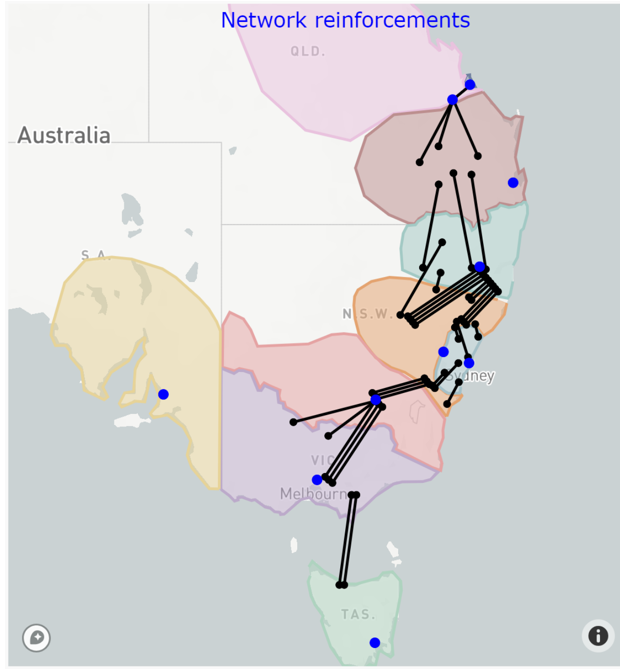


Figure 4.6: Candidate network reinforcements considered for the case study applications.

Table 4.5: Parameters of candidate utility-scale BESS.

Region	Tech.	Charging capacity [MW]	Duration [hr]	Lifetime [yr]	Expansion modules
All	BESS	50	4	20	200

Following AEMO's assumptions, storage investment costs decrease over time, and depending on each scenario, they follow a specific trajectory as the years go by. Table 4.6 presents the evolution of storage investment costs according to the scenarios and years considered for the problem modelling.

Table 4.6: Investment costs of candidate utility-scale BESS.

Scenario	Region	Investment cost [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

Finally, it is important to note that the proposed model has the features to be expanded and consider generation expansion decisions. However, as explained above, the generation fleet and its evolution over time are obtained directly from the ISP results, and those values are handled as input data to the model.

4.1.3.3. Multi-stage scenario tree

The multi-stage scenario tree employed in the problem formulation is displayed in Figure 4.7. This tree [64] was built upon the four scenarios devised by AEMO for the 2022 Integrated System Plan [7], previously described in Section 4.1.2: *Slow Change*, *Progressive Change*, *Step Change*, and *Hydrogen Superpower*, with the objective to create a more complex and granular representation of future long-term uncertainty. Furthermore, the estimated likelihoods associated with each scenario correspond to those described in Table A.1.

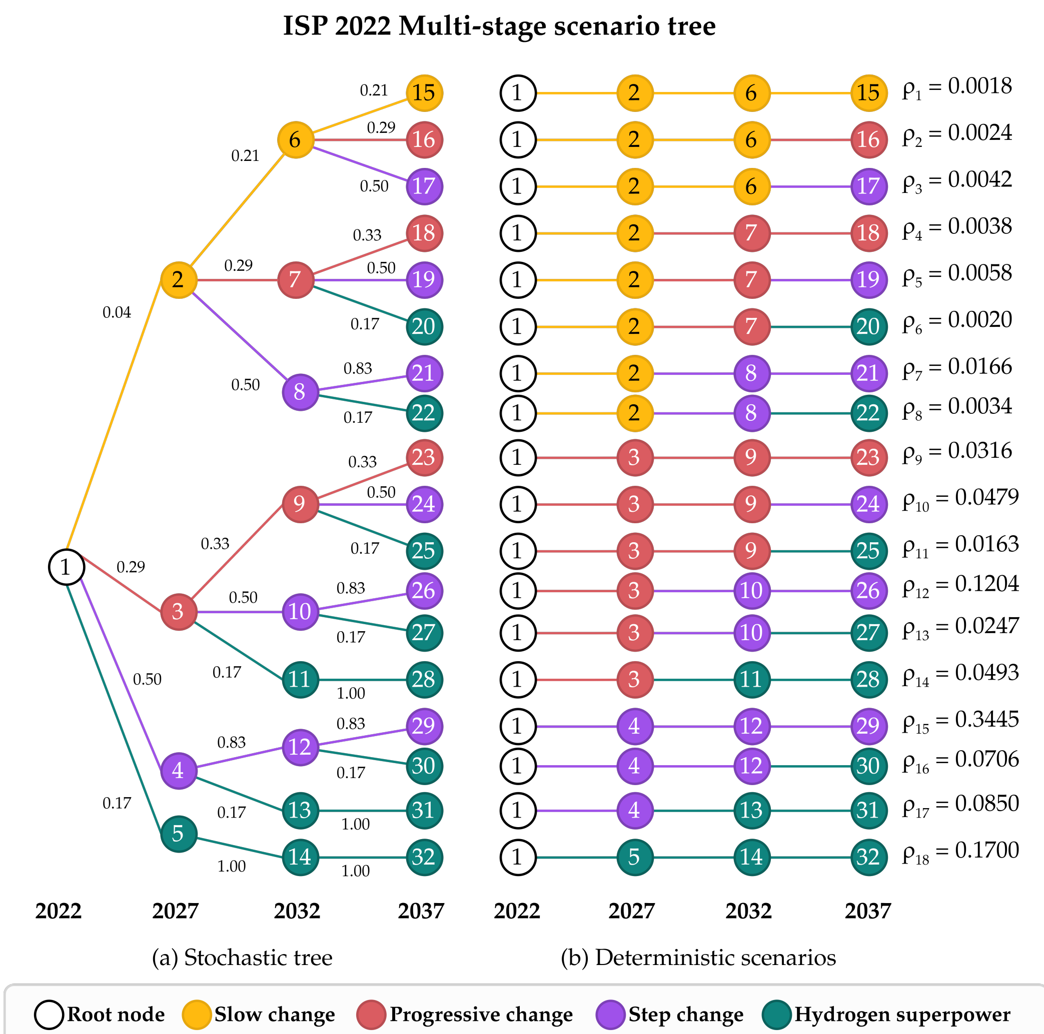


Figure 4.7: Multi-stage scenario tree for the 2022 ISP and deterministic scenarios.

To refine the scenario tree and emulate future transitions between scenarios, intermediate incremental scenarios were created based on the information provided for the original four scenarios, resulting in 18 scenarios, as illustrated in Figure 4.7. The probabilities for the transitions are determined using an approach based on the probabilities assigned to the four original scenarios, where the values are computed by considering the number of child nodes for each node in the tree [8].

For the case study applications of this work, the decision-making architecture makes decisions every five years, corresponding to the considered epochs represented in the scenario tree. These epochs (2022, 2027, 2032, 2037) are directly linked to the lead time of the transmission candidate options. Although the 5-year approach was adopted to model the investment decisions, the decision-making architecture and the employed tree can be easily modified to create a different future representation.

The scenarios encapsulate varying degrees of long-term uncertainty across several critical parameters, including load growth, VRE, retirement of coal units, fuel and investment costs, and DER adoption. These uncertainties are further described through Figures 4.8, 4.9, and 4.10. Figure 4.8 shows the installed capacity of the different technologies across the scenarios under consideration. Furthermore, Figure 4.9 depicts the specific evolution paths for the installed capacity of DER, the main object of study in this work. Figure 4.10 describes each scenario's expected yearly energy consumption. Annex E further describes each scenario within the scenario tree and breaks down the nodes of the tree and its probabilities.

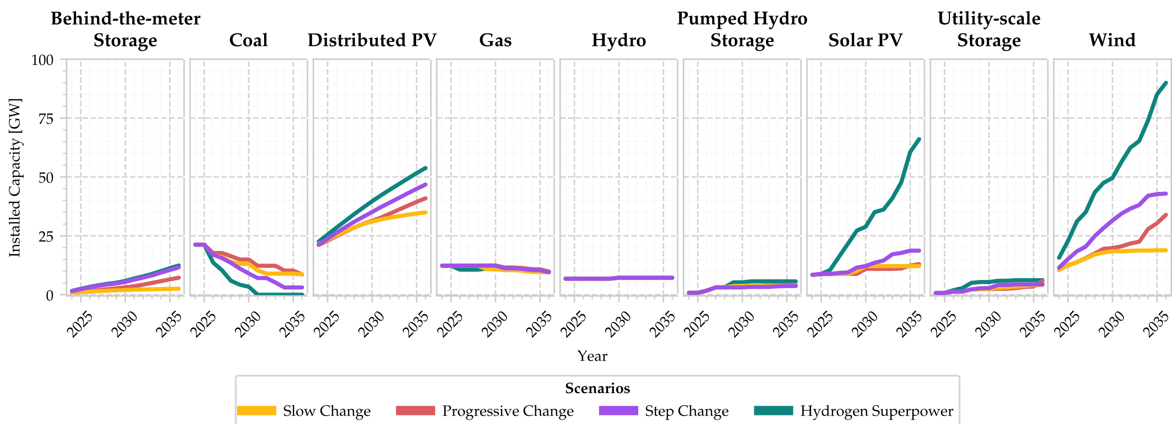
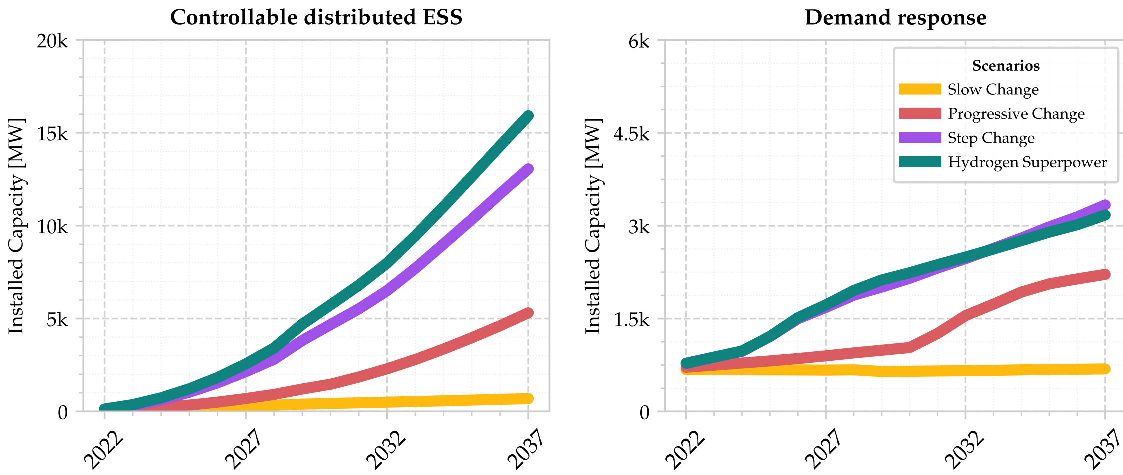


Figure 4.8: Projections for installed capacity by technology and scenario in the 2022 ISP.

As explained in [29], all uncertain parameters considered for the presented modelling (load growth, renewable energy and DER deployment, retirement of coal units, and investment and fuel costs) are sources of deep uncertainty, underscoring the applicability of the proposed approach under a context of this nature. Furthermore, following the definitions presented in the literature survey introduced in Section 2.2.2, the multi-stage modelling would allow decision-makers to deal with deep uncertainties by providing flexible, adaptive decisions for each original scenario as well as for all potential incremental transitions, which are plausible but divergent possible states of the world, establishing multiple long-term development paths with a common initial *here-and-now* investment portfolio and different sets of *wait-and-see* investment decisions for each unfolding future.



(a) Controllable distributed energy storage (b) Demand response

Figure 4.9: Projections for the installed capacity of distributed energy resources in the NEM.

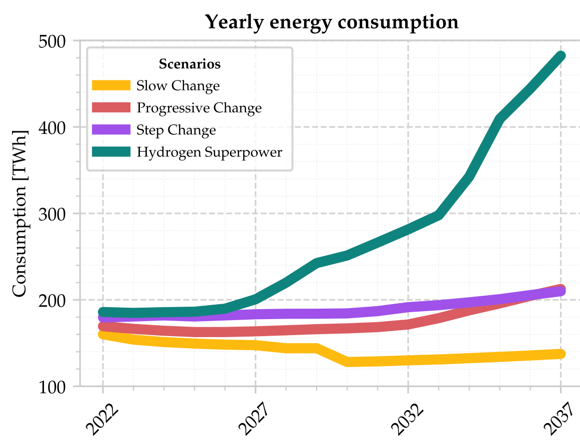


Figure 4.10: Expected yearly energy consumption for each scenario of the 2022 ISP.

4.1.3.4. Operational data

To ensure efficient computation time preserving operational detail, each year under analysis is represented by a subset of representative weeks. This balances computation time with an accurate representation of the operation of the system [65, 66]. This approach avoids the burden of simulating all 52 weeks while capturing key system dynamics. Within each representative week, operational decisions are made in hourly steps (1-hour timesteps), resulting in 168 periods for each node n of the scenario tree. These representative weeks are selected from the 52 available in a year based on their demand profiles and renewable energy availability, ensuring coverage of peak and average periods at system and state levels. The number of selected weeks can be adjusted depending on study requirements and computational resources available. Further details regarding the specific weeks chosen for each node are provided in Annex D.

4.2. Description of case studies

This work's case studies seek to illustrate and assess the impact of controllable distributed energy resources (DER) on system expansion decisions, particularly in transmission lines and utility-scale energy storage. The technologies considered as controllable DER are distributed energy storage and demand response.

Four case studies are conducted to analyse the impact of these technologies in power system planning. The cases consider two main distinctive elements: *(i)* the candidate technologies available for system expansion: only transmission or joint expansion of transmission and storage, and *(ii)* the ability of DER to be controllable, that is, whether they are dispatchable through an aggregator (active market participants) or if they are considered as passive "behind-the-meter" elements, having no interactions with the market. Therefore, the four proposed case studies are the following:

- **Base case:** Only investment in transmission lines, DER are non-controllable.
- **Case #1:** Investment in transmission lines and energy storage, DER are non-controllable.
- **Case #2:** Only investment in transmission lines, DER are controllable.
- **Case #3:** Investment in transmission lines and energy storage, DER are controllable.

In addition, the case studies aim to study the advantages of employing the proposed multi-stage stochastic planning framework to design investment portfolios and compare its techno-economic performance with a deterministic planning approach through various metrics. For each of the four detailed case studies, the portfolios resulting from the *stochastic* and *deterministic* approach are studied, comparing their respective outcomes. To fully understand the case studies and subsequent results, it is important to provide detail regarding what is understood for a *stochastic* and a *deterministic* approach:

- *Stochastic modelling:* The stochastic modelling considers the incorporation of long-term uncertainties for various parameters (these uncertainties include the retirement of coal-fired units, adoption of VRE, deployment of DER, fuel prices, deployment of ESS, investment costs and load growth) through the scenario tree shown in Figure 4.7 (a). This tree comprises 32 nodes spread across four investment periods, resulting in 18 scenarios. Investment decisions are made for each node, and infrastructures become available based on associated lead times.
- *Deterministic modelling:* The deterministic modelling approach considers the same 18 scenarios generated via the scenario tree, but assuming "perfect" information about the future, i.e. uncertainties associated with the potential unfolding of more than one scenario, are not considered, as shown in Figure 4.7 (b). In other words, the decisions to deploy new infrastructure are optimised for every scenario independently, generating 18 independent optimal portfolios assuming a perfect forecast for the abovementioned parameters.

Chapter 5

Results and discussion

This section presents and analyses the results obtained by applying the multi-stage stochastic expansion model proposed in Chapter 3 to the case studies detailed previously in Section 4.2. The system model, input data, and multi-stage scenario tree presented in Chapter 4 are used to solve the problem. For each case, the eighteen scenarios of the proposed scenario tree (Figure 4.7) are solved, and the investment portfolios in transmission and energy storage (if applicable to the case) and the information on operational, investment, and total costs are obtained.

Throughout the section, a comparative analysis of the cases in terms of costs is carried out to determine the impact of the participation of DER in the expansion planning problem and the advantages of employing the proposed stochastic model. Subsequently, the chapter delves into the specific effects of the involvement of active DER in the operation of the system, exploring their implications in displacing or delaying investments in transmission and utility-scale energy storage. Furthermore, the section reviews how the chosen modelling approach, whether stochastic or deterministic, reshapes the investment decisions and how each methodology leverages the emerging flexibility from DER to inform short- and long-term system planning decisions.

5.1. General techno-economic results

Table 5.1 summarises the techno-economic results for each case study and modelling approach (deterministic or stochastic). Specifically, for the deterministic approach, the expected costs are calculated by summing the weighted values of the total cost of each scenario and its likelihood for all eighteen scenarios. The table provides a breakdown of the total expected costs into expected investment and operational costs to understand the impact of different technologies in the expansion decisions. The table also shows key metrics, such as the most expensive scenario across the eighteen scenarios analysed for each case and the maximum installed capacity of transmission and storage at the end of the period under analysis. Annex F provides a deeper analysis of the obtained investment portfolios.

Furthermore, Figure 5.1 shows the probability distribution of expected costs for both planning approaches when applying the stochastic model, namely transmission only and transmission plus storage, in order to understand the impact of the increased flexibility from DER in the total system costs and costs of scenarios. Each dot in the distribution corresponds to the pair between cost and cumulated probability associated with each scenario.

Table 5.1: Summary of results for the cases considered.

Item	**Base case** (NC + TX)[a]		**Case #1** (NC + TX + BESS)		**Case #2** (C + TX)		**Case #3** (C + TX + BESS)	
	Det.	***Stoch.***	***Det.***	***Stoch.***	***Det.***	***Stoch.***	***Det.***	***Stoch.***
Expected investment cost [$bn]	4.33	5.0	4.13	5.33	3.24	4.27	3.07	3.6
Expected operational cost [$bn]	29.46	29.45	25.92	25.49	25.03	24.82	25.01	25.19
Total expected cost [$bn]	33.79	34.45	30.04	30.82	28.26	29.09	28.08	28.79
Most expensive scenario	13 (39.53$bn)	13 (39.81$bn)	13 (34.21$bn)	13 (34.44$bn)	13 (31.90$bn)	8 (35.58$bn)	13 (31.69$bn)	13 (33.49$bn)
Maximum transmission installed [MW]	19 770	17 020	17 020	17 020	16 120	17 020	15 520	8 650
Maximum storage installed [MW]	–	–	6 200	8 600	–	–	1 400	5 300

[a] NC: *non-controllable DER* / C: *controllable DER* / TX: *investment in transmission* / BESS: *investment in energy storage.*

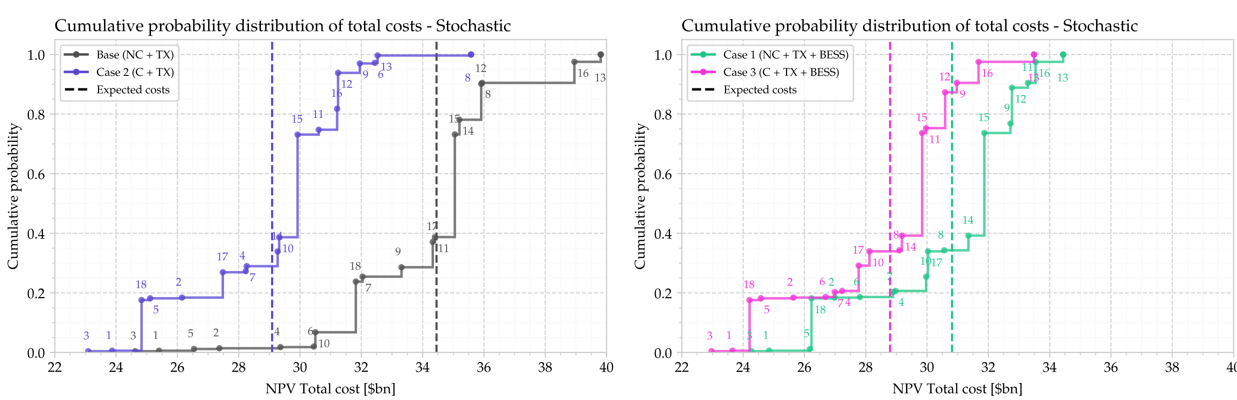
From the results presented in Table 5.1 for the stochastic approach, the base case has the highest expected total cost, with $34.45 billion over the entire planning horizon. This is due to the lower flexibility available for system operation since the controllability of DER is not enabled, and there is no possibility of investing in BESS. For the other cases, the expected costs decrease as they include the controllability of DER and the option of investing in BESS.

It is important to note that in Case #2, when DER are controllable, but investment in storage is not allowed, lower expected costs are obtained compared to Case #1, when investment in storage is considered, but DER are not controllable. This highlights the positive impact enabling the controllability of DER can have on the total expected costs of the system, even surpassing the savings new utility-scale storage can make. Case #3 yields the lowest expected costs, with $28.79 billion. In this case, the model can invest in transmission lines and energy storage and assumes DER are controllable. Thus, by leveraging the operational flexibility from DER while investing in additional energy storage (but less than in Case #1) and reducing the total capacity invested in transmission lines, the total expected costs are minimised, keeping the expected operational costs in the same order of magnitude compared to the other cases ($25 billion), but with fewer new transmission investments. This behaviour of the costs is attributed to the ability of DER to manage load patterns, thus reducing congestion in the transmission network and the need for energy arbitrage.

Regarding the deterministic approach, the same trend of decreasing costs is observed: when more flexible technologies are available for the system's operation, costs decrease, and fewer network investments are required. It is important to note that, in every case study, the stochastic approach has higher total expected costs than the deterministic approach. This is because the stochastic model considers what is best for *all* scenarios across the scenario tree, leading to an investment portfolio that seeks to cover all scenarios in the best possible way, potentially leading to higher investment costs. In contrast, the deterministic model adjusts the investment portfolio in each scenario for the specific future each scenario "sees", making fewer investments but posing a higher risk in the face of potential changes in the future conditions that the system is subject to.

Table 5.1 shows that the expected investment costs for the stochastic approach are higher than the deterministic for all cases analysed. This points to the fact that the stochastic model produces a solution that hedges against uncertainty through increased investments in new network assets. A solution of this nature potentially delivers higher coverage across a broader range of scenarios while minimising the risks of unfavourable outcomes from inadequate investment decisions when facing a future with multiple uncertainties. Moreover, when employing the stochastic model, the expected operational costs for the base case and cases #1 and #2 are lower than the deterministic model. This demonstrates that the stochastic approach makes more investments to reduce the expected operational costs.

Regarding Case #3, where DER are controllable, and investments in transmission and storage are allowed, although the expected investment costs continue to be higher in the stochastic model ($3.6 bn as opposed to $3.07 bn in the deterministic model), operational costs are also higher when compared to the deterministic approach. This is because the stochastic model relies more on the flexibility provided by DER, which comes at a cost for the system operation. This additional cost results in an increase in operational expenses to minimise the total expected costs. However, this also means that the model reduces the need for investments in bulk assets compared to Case #1, where storage is an investment option, but DER are not controllable. This indicates that the stochastic model places a high value on DER flexibility for the system's operation, thus reducing the need for new transmission lines or energy storage investment and minimising the risk of stranded assets in the long term.



(a) Transmission expansion only

(b) Transmission and storage expansion

Figure 5.1: Total expected costs and costs by scenario for the expansion of the system considering the controllability of DER - stochastic model.

In three out of four cases for the stochastic model, scenario 13 is the most expensive. As can be seen in the scenario tree, this is the one with more transitions (a potential risk a power system can face), moving from *Progressive Change* in 2027 to *Step Change* in 2032 and finally to *Hydrogen Superpower* in 2037. The costs of this scenario decrease when the DER are controllable, and investment in storage is possible. This highlights the ability of DER, and in general of flexible technologies, not only to reduce the expected costs of the system but also to play a role in shifting the right tail of the cost distribution (the most expensive scenarios). This can be further seen in Figure 5.1.a, where not only do the expected costs shift to the left when controllability is enabled (expected costs reduce by $5.36 bn.), but also the most expensive scenarios, such as numbers 12, 13, and 16 (e.g. scenario 13 shifts from $39.81 bn in the base case to $32.53 bn in case #2). When the model can also invest in energy storage (see Figure 5.1.b), this leftward shift is less pronounced since the additional investment in BESS inherently reduces the costs of both cases. Even so, the flexibility from DER allows the tail to be moved to the left as well as the expected costs of the distribution (a reduction of $2.03bn is obtained).

5.2. The impact of DER flexibility on deterministic and stochastic planning

Figure 5.1 presented the cost results of employing stochastic planning in various case studies that considered different assumptions associated with the controllability of DER and the model's possibility to invest in transmission and/or energy storage. The results obtained for the different cases and corresponding scenarios range from $23bn for scenario 3 when DER are controllable and can reach values close to $40bn in scenario 13 when DER are not controllable, and the model can only make investments in the transmission system.

One study that can be carried out is to compare the effect that the controllability of DER has on investment portfolios when employing deterministic planning (in particular, applying LWR as a method to choose a unique optimal portfolio) or stochastic planning. This will allow for determining the optimal configuration of the required investments and the impact of the flexibility coming from these assets on the total system costs. In particular, the optimal portfolios, or equivalently, the optimal development paths obtained from each planning approach, can substantially differ in where, when, and how much capacity is installed. Consequently, the decisions made from these investment paths will directly impact the future operation of the system due to the need for anticipatory investments to accommodate a high penetration of renewable generation or deployment of DER that is projected in specific scenarios.

Thus, this section presents a quantitative comparison between an optimal development path (ODP) obtained through deterministic-based LWR metrics and the presented stochastic planning approach. The main aim is to understand the advantages and disadvantages of each approach with particular attention to the impact of the flexibility from DER on investment decisions. In particular, the methodology for determining the ODP through LWR is detailed and exemplified in [40]. In addition, the deterministic scenarios considered come from the disaggregation of the 18 scenarios that give form to the 32-node scenario tree presented in Figure 4.7. This figure also presents the formation of the deterministic scenarios.

This analysis employs the case where DER are controllable, and investments in transmission and battery energy storage are allowed. The resulting cost and regret matrices are presented in Figure 5.2. The left matrix presents the costs of running each scenario against each portfolio (development path) generated deterministically. The right matrix corresponds to the regrets of each scenario, i.e., the difference between employing the original portfolio generated for the scenario (the value of the diagonal) versus fixing a given portfolio.

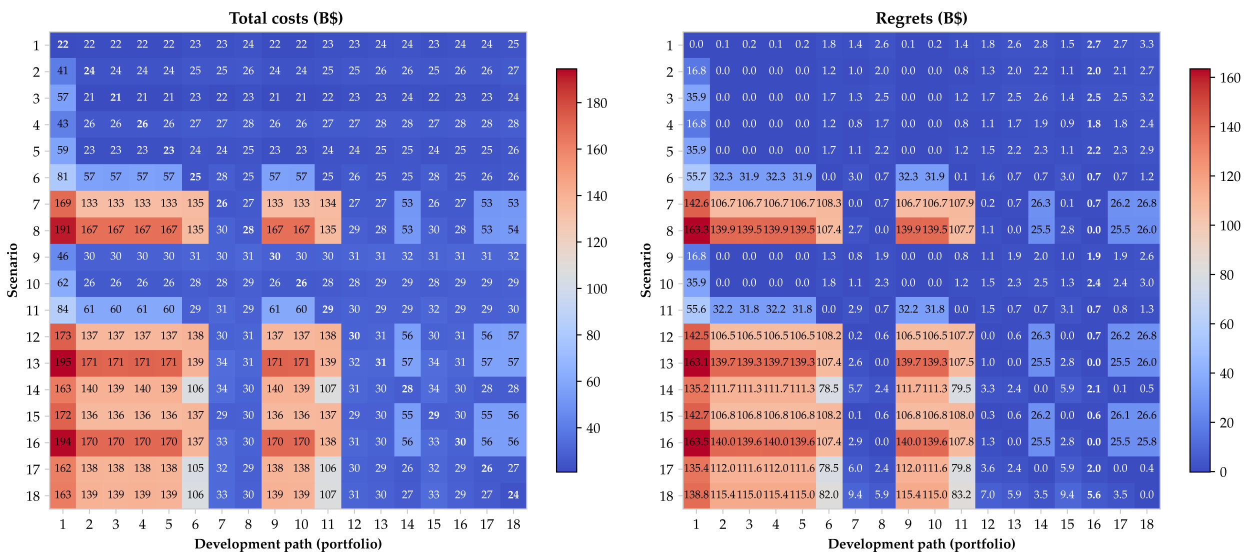


Figure 5.2: Performance of deterministic portfolios (development paths) in each of the analysed scenarios and regret calculations.

The numbers in each matrix have been rounded to the closest integer value for a more straightforward interpretation of the results. The diagonal represents the total cost found in the process of determining the development paths for each scenario. In this case, the development path found for scenario 16 is chosen through the LWR metric as one that produces the lower maximum regrets (the same development path was found by applying the LWWR metric). As seen in the scenario tree, this scenario (scenario number 16) corresponds to Step Change, but the Hydrogen Superpower scenario unfolds in the final stage (2037). The infrastructure deployment for this scenario across the years is presented in Figure 5.3 for the deterministic approach. For comparison purposes, the optimal development path resulting from the stochastic case for this exact scenario is presented in Figure 5.4.

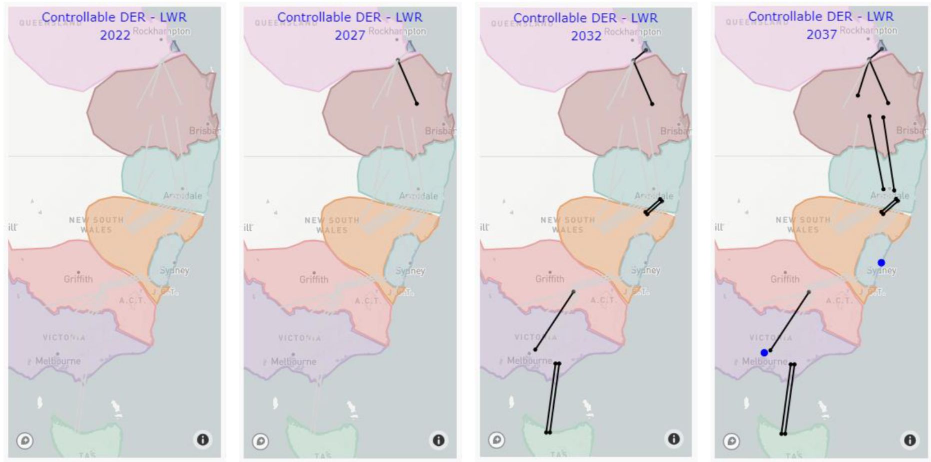


Figure 5.3: Best deterministic optimal path (development path 16) covering years 2022, 2027, 2032 and 2037 from left to right. Controllable DER case.

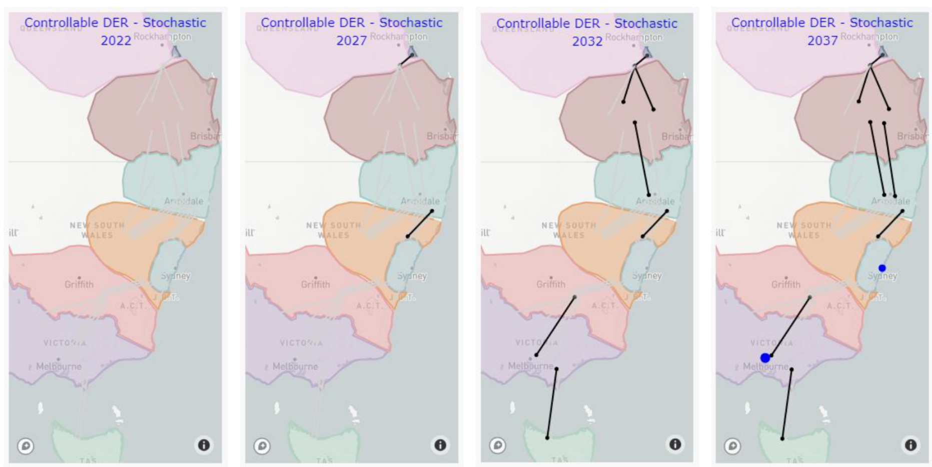


Figure 5.4: Optimal development path for the stochastic scenario number 16, covering years 2022, 2027, 2032 and 2037 from left to right. Controllable DER case.

Figure 5.3 shows that the LWR approach decides on a single transmission reinforcement in 2022 (available in 2027), which corresponds to SQ-CNQ Option 2, with a capacity of 300 MW, while the stochastic approach requires two reinforcements CNQ-GG Option 1 and CNSW-NNSW Option 7, leading to a total installed capacity of 2,140 MW in 2027. At first glance, this might be interpreted as an advantage of the LWR approach since it requires less short-term investment, thus reducing investment costs in the present. However, this may not necessarily be accurate when considering the long-term outcomes for the system.

Looking forward to the year 2032, through the LWR approach shown in Figure 5.3, the reinforcement of five transmission corridors is observed, namely CNQ-GG, CNQ-SQ, NNSW-CNSW, SNSW-VIC and TAS-VIC, giving a clear indication of the system needs in terms of reinforcements required in the transmission network. Moreover, in Figure 5.4, the stochastic model reinforces the five corridors mentioned above plus the corridor SQ-NNSW, revealing in advance the required additional capacity for that link in 2032 instead of 2037, as observed in the results from LWR. This result is of key importance because the stochastic framework could reveal the need for early reinforcements (anticipatory investment) to accommodate the increasing production of renewables north of the NEM. At the same time, the early construction of infrastructure (and, therefore, early decision-making) could bring more flexibility to the planner for further developments.

It can be established that, for this study, the scenario tree depicted in Figure 4.7 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 independent representations of the future rather than a cohesive perspective. Therefore, the performance of the optimal portfolio identified through the LWR metric (Figure 5.3) should be evaluated within the representation of the future outlined in the scenario tree. Figure 5.2 already reflects this result, specifically in the column related to the costs of considering candidate development path number 16 across scenarios. Furthermore, Figure 5.5 shows the cumulative probability distribution of costs derived from the optimal development path determined by the LWR metric and the corresponding cost distribution for the stochastic approach in the same case. It is possible to see that against the representation of the future modelled by the scenario tree, the investment path resulting from the LWR approach yields results in which the expected costs of investment in new assets and the operation are \$0.8 billion more expensive than the stochastic approach, underscoring that a portfolio resulting from employing the stochastic approach can perform better in terms of expected costs against multiple futures. This is explained by the explicit modelling of uncertainty in this approach, in contrast to what is done through LWR, where uncertainties associated with different parameters are not proactively considered in obtaining candidate investment portfolios.

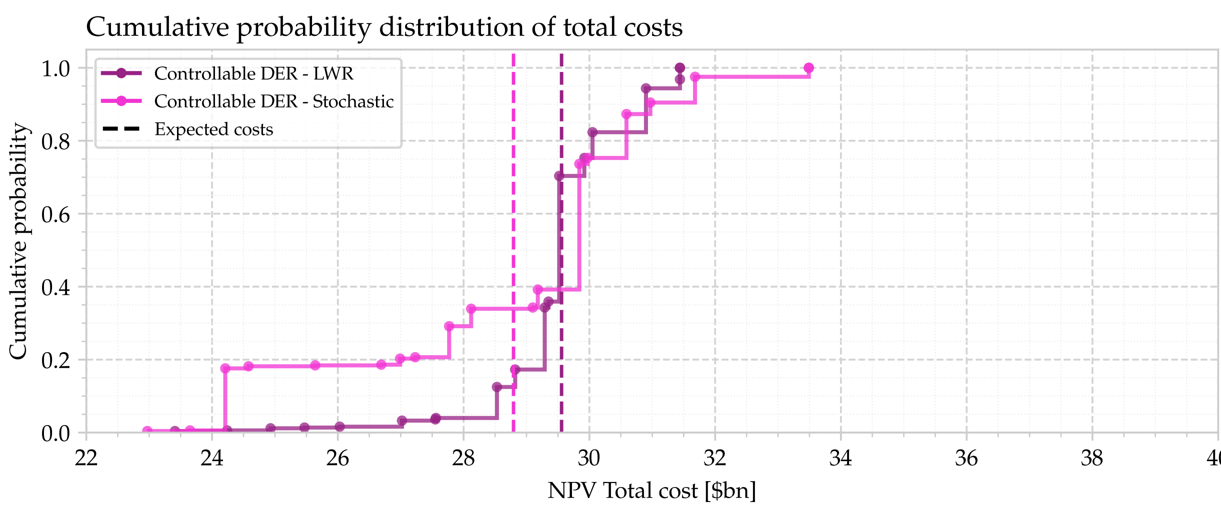
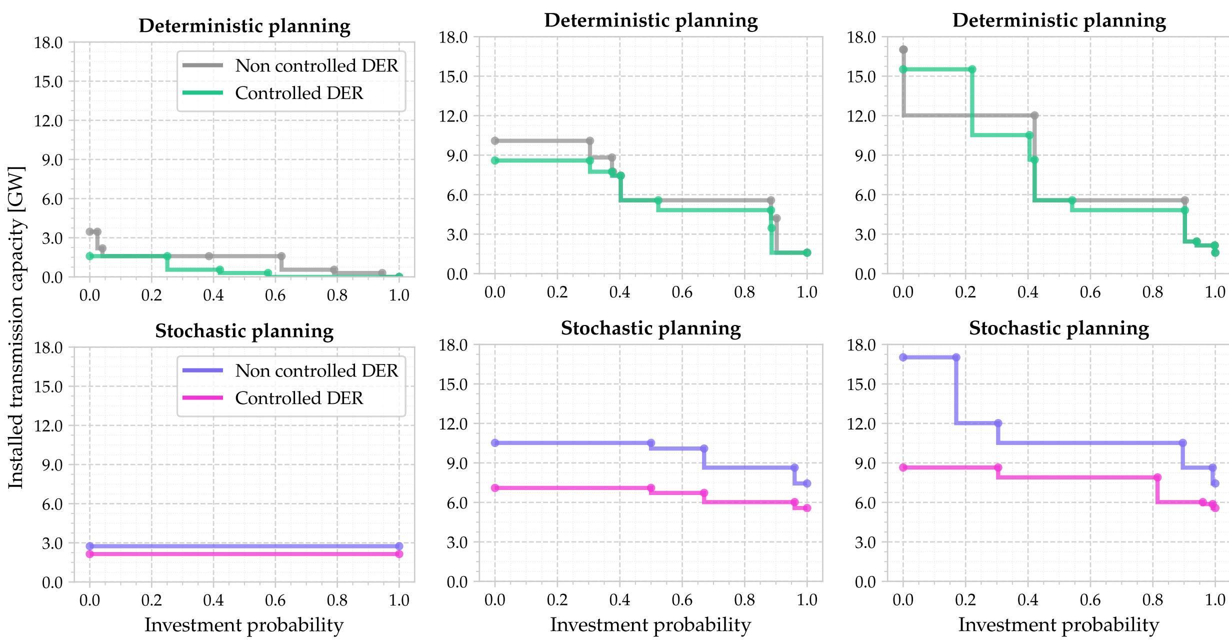


Figure 5.5: Cumulative probability distribution of costs per scenario. Comparison between optimal development path obtained through LWR and stochastic model.

5.3. Impact of DER controllability on transmission investments

This section explores how flexible distributed energy resources (DER), impact the investment portfolios in transmission lines from an aggregated perspective. Also, an assessment regarding how the employed modelling framework, whether stochastic or deterministic, evaluates and recognises this enhanced demand-side flexibility. The results from Cases #1 and #3 are employed for analysis purposes. These cases consider investment in transmission and storage, as these were found to be the most optimal for the system's operation in terms of costs.

To conduct the analysis, the investment probabilities of aggregated transmission line capacity are computed for each case, summarising the results for the eighteen scenarios considered. The investment probability can be understood as the likelihood of an (or a set of) investment candidate(s) to be built across scenarios (e.g. 5000 MW with 50% of investment probability means that with 50% probability that capacity is built within a particular year). Figure 5.6 consolidates these results for each planning approach (deterministic or stochastic), case and investment year. Each sub-figure shows the probability of building a given aggregated transmission line capacity, which is the sum of the capacities of all lines built in each investment year (epoch).



(a) Transmission investments 2027

(b) Transmission investments 2032

(c) Transmission investments 2037

Figure 5.6: Transmission investment results for each stage and modelling approach.

As can be observed in Figure 5.6, when employing the deterministic planning approach, enabling DER controllability reduces expected installed transmission capacity by 37%, 11% and 8% in the respective investment years (2027, 2032 and 2037), as also described in Table 5.2. Given these results and the corresponding probability distribution from Figure 5.6, it is essential to note that to reduce transmission investments, this approach highly values the flexibility of controllable DER in the first stage of investment and less in subsequent stages (2032 and 2037). An investment portfolio of this nature could translate into a higher investment risk (e.g., late transmission built may not be enough for an optimal operation of the system) because the deployment of a higher capacity of controllable DER, and therefore, higher operational flexibility, is expected to occur in the long term, towards 2037, rather than in the short term, as previously detailed in Figure 4.9.

Table 5.2: Percentage of the expected reduction in investments in transmission capacity.

Approach	Stage 2 - 2027	Stage 3 - 2032	Stage 4 - 2037
Deterministic	37%	11%	8%
Stochastic	22%	31%	31%

In particular, the transmission infrastructure decided to be built in 2022 (which becomes available in 2027) risks not being feasible in the range of all other scenarios in the subsequent stages when the deterministic model is employed. This is because in a further transition between scenarios (e.g., from *Slow Change* to *Step Change* in 2032 due to increased development of renewable generation projects), the line that is decided not to be built in the first epoch (NNSW-SQ Option 1) could be critical to allow the transport of renewable energy between the northern states (QLD and NSW) in later stages, which would not be possible due to the lead time of the transmission projects, thus increasing system congestions and consequently the total costs.

Compared to the deterministic approach, the stochastic model shows a reduction of 22% in the expected installed transmission capacity for 2027 and 31% for 2032 and 2037. This means the stochastic approach is more conservative regarding DER flexibility to defer investments in the first investment stage, but shows a higher reliance on controllable DER to reduce transmission investments in later stages. Furthermore, these results showcase the advantages of the proposed stochastic model in capturing the growth of DER controllability, because the deployment is expected to be higher in the long than short term.

In addition, the stochastic model shows that when DER controllability is not enabled, there is a probability of 30% of making a conservative decision to build significantly more transmission capacity (17.5 GW or 12 GW instead of 9 GW), as indicated by the purple curve in Figure 5.6c. However, these investments are not made when DER are controllable, as seen in the pink curve of Figure 5.6c. Indeed, the stochastic model unlocks a risk-hedging value from the controllability of flexible technologies so that the investments that do not have a high probability are displaced, reducing the potential risk of having stranded assets.

5.4. Range of transmission expansion requirements

This section studies how the range of transport investment capacity varies in the case that DER controllability is enabled. The main objective is to assess how DER controllability affects the robustness and potential risk of investment portfolios, and how deterministic or stochastic optimisation approaches evaluate this feature. Figure 5.7 shows the results corresponding to the range of aggregated transmission capacity built for each case (cases #1 and #3 for both deterministic and stochastic approaches). The range metric blends the values of transmission capacity constructed in all scenarios//. The higher the range, the more dispersed the investment needs are in the scenarios analysed.

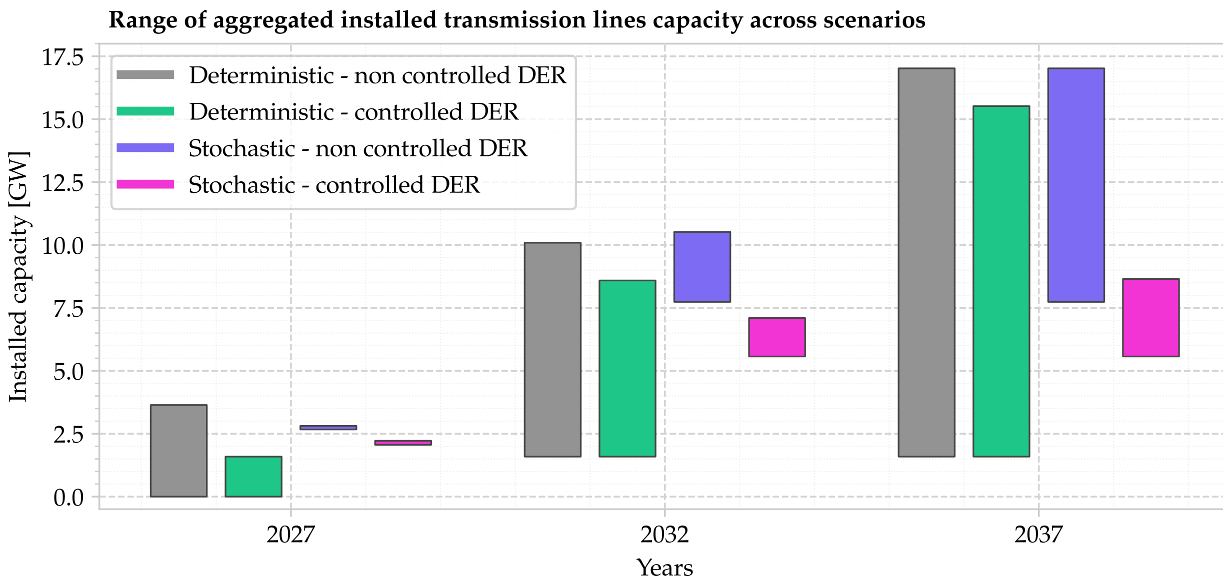


Figure 5.7: Minimum and maximum expansion of capacity in transmission lines - cases #1 and #3.

For example, in the year 2032, the deterministic model (grey and green bars) built at least 1,590 MW across all 18 scenarios, which is depicted in the lower boundary of the bar. On the other hand, the maximum (upper limit) indicates the maximum installed capacity in at least one of the scenarios (the other scenarios build the same or less). For example, in the same year, 2032, the deterministic model yields 10,090 MW of transmission built when DER are non-controllable, while 8,590 MW are built when they are controllable.

In particular, the *here-and-now* decisions to build the infrastructure that becomes available in 2027 are of crucial importance. When employing the deterministic model, the transmission capacity that becomes available in that year (2027) varies from 0 to 3,460 MW in the case when DER are not controllable (grey bar). This extensive range of installed transmission capacities indicates low short-term certainty regarding the required expansions across scenarios. This causes investments to be undertaken with higher risks, even when DER are controllable (green bar) because the different scenarios' installed capacities also vary from 0 MW to 1,590 MW. This gives low certainty to the planner as to which project needs to start building today.

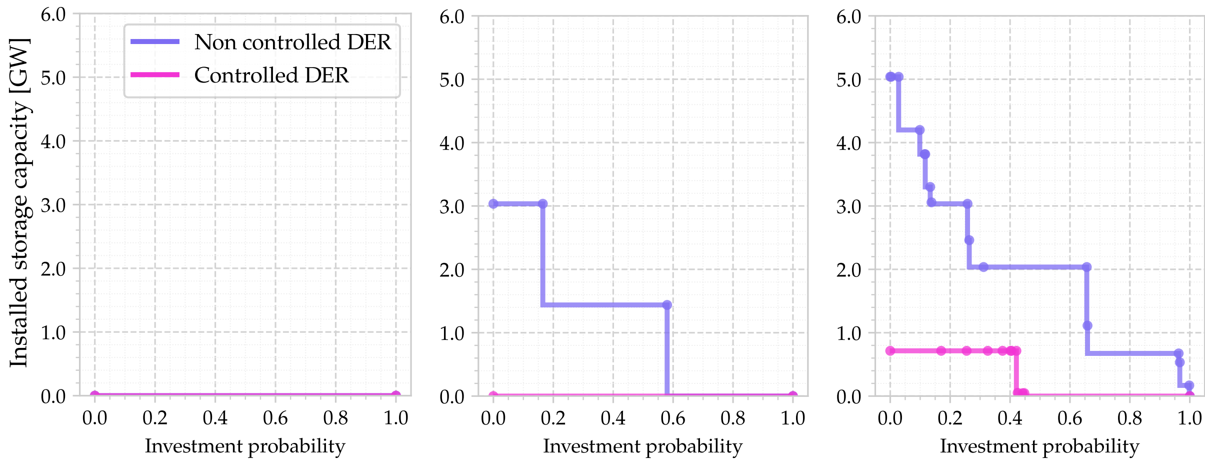
Looking into the results for the stochastic model with non-controllable DER (purple bar), the capacity available in 2027 is exactly 2,740 MW, giving the planner a reliable answer about the investments the system requires to start building today. Furthermore, when DER controllability is enabled (pink bar), 2,140 MW are installed, which is higher than the installed capacity in all deterministic scenarios. Thus, the model extracts risk-hedging value from the controllable DER technologies to reduce 600 MW of transmission to be built while maintaining its ability to provide high certainty regarding the necessary expansions in the first investment stage because all the scenarios install 2,140 MW. This reduces doubts regarding the system's capacity for transmission expansion across all scenarios.

Moreover, the path of investments resulting from employing the stochastic model presents a higher stability and anticipativity over time. This characteristic refers to the ability of the investment plan to perform well under various scenarios, reducing the planner regret of having stranded assets in the face of potential overestimations. In particular, the case for the stochastic model with controllable DER (pink bars) presents the lowest range in every case (5,570 MW to 8,650 MW in 2037) by the end of the period under analysis. This result stems from the ability of the stochastic model to consider what benefits *all* scenarios, leading to a compromise solution. In contrast, deterministic practices yield portfolios tailored to specific scenarios, increasing the risk of investment inefficiencies, as observed in the results of Figure 5.7. For instance, in the deterministic approach, when DER are controllable, the range of investments is extensive, varying between 1,590 MW and 15,520 MW, indicating little certainty regarding the compulsory transmission investments the system requires.

5.5. Assessing DER on displacing storage investments

This section aims to understand the interplay among the different sources that provide operational flexibility to the system (in this case, DER and new BESS) and how these interactions influence expansion decisions and total costs of the system, particularly in a system that is transitioning to have a considerable amount of controllable distributed storage installed. Figure 5.8 summarises the results of the stochastic model for additional utility-scale storage (BESS) installed in cases #1 and #3.

In the studied cases, DER are expected to have an increased deployment towards the end of the period under analysis, as shown in Figure 4.9. Based on the results, for the case of non-controlled DER in Figure 5.8 (c), up to 5.4 GW of new BESS are deployed in the 3rd stage (2032) for scenario 14, while other scenarios install less (an expected average of 3200 MW). On the other hand, due to the progressive integration of controllable DER in the pink curve of Figure 5.8, new storage investments are mostly delayed to 2037 because the controllability of DER also allows for energy arbitrage purposes, reducing the average installed to 900 MW. As shown in Figure 5.8 (c), in the final stage (2037), BESS are built in both cases, but with an expected reduction of 82% of installed capacity across scenarios when controllability is enabled, thereby highlighting the impact of considering the deployment of controllable DER in reducing investments in new energy storage.



(a) Storage investments 2027

(b) Storage investments 2032

(c) Storage investments 2037

Figure 5.8: Probability distribution of battery storage investments - stochastic model.

Another important point to analyse is the interplay between storage and batteries concerning cost reduction. As previously discussed, the major contribution of energy storage is to reduce the system costs rather than to displace large amounts of transmission investments in the optimal portfolios. To better understand the impact of enabling the controllability of DER in the savings the investment in new BESS can yield, Figure 5.9 shows a comparison of the expected system cost reduction when investing in batteries.

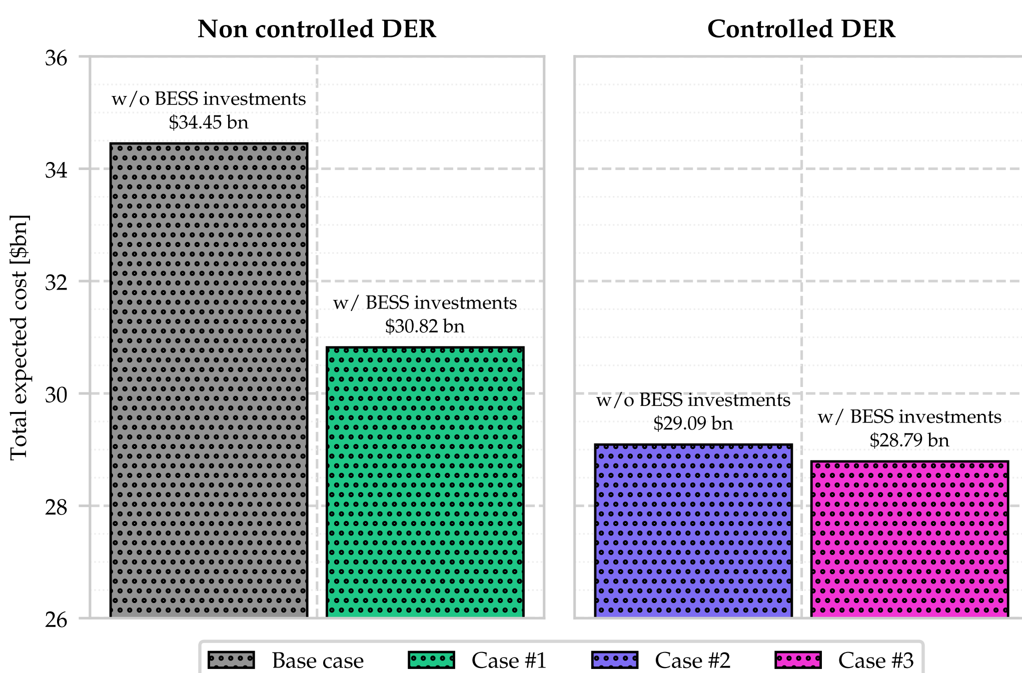


Figure 5.9: Total expected cost comparison to analyse the impact of DER in the economic benefits delivered by BESS.

It is clear to see that when DER are non-controllable, the impact of new energy storage on cost reduction is higher than when they are controllable, which is directly explained by the fact that when controllability exists, the model directly invests in less storage. Specifically, when DER are not controllable, the savings from additional storage amount to \$3.63 billion, while when they are controllable, this figure is reduced to \$0.3 billion. Thus, by enabling the controllability of DER, the model installs less storage, which results in lower system operating cost savings from this technology. Therefore, DER acts as a direct substitute for storage.

Chapter 6

Conclusions and further work

This work presented a comprehensive multi-stage framework for power system expansion planning under uncertainty with an active model for controllable DER, allowing for modelling different flexible technologies emerging from the consumer side into the planning problem. Additionally, the model included a detailed long-term uncertainty representation and operational constraints for synchronous units, energy storage and system reserves, allowing for a more accurate valuation of the flexibility different technologies can provide to the system's operation. Four case studies within the Australian NEM were discussed and analysed, employing a highly granular representation of future uncertainties through a four-stage scenario tree. The case studies assessed and highlighted the potential and impact of DER in economically displacing investments in transmission lines and energy storage and the effects of unfolding deep uncertainties through the decision-making process for the system's expansion.

The results demonstrated that selecting a stochastic mathematical framework is essential for progressively unlocking the risk-hedging value of controllable DER to define adequate system investment plans. The analysis shows that a deterministic model places a higher value on DER controllability for displacing network investments in the initial investment stage while neglecting the long-term flexibility that controllable DER could provide. In contrast, the proposed stochastic model steadily integrates the increasing controllability of DER into investment decisions made during all the stages, taking into account the higher DER penetration towards the end of the planning horizon.

The analysis also shows that the stochastic model allows for narrowing down the investment candidates the planner should consider building in further stages. The range of built investment candidates is further narrowed down when controllable DER are enabled. Furthermore, the installation of utility-scale BESS is significantly reduced by 82% when enabling DER controllability, providing insight for policymakers to design incentives for DER deployment for energy arbitrage purposes. Given that the deployment of energy storage is faster than other technologies and can be installed after uncertainties are revealed in each scenario (BESS have no lead time), BESS serve as a complementary technology to transmission investments. Conversely, as the deployment of DER is part of the uncertainties the model deals with, and there is a considerable capacity available in the future, these technologies may postpone or discard building certain transmission assets.

6.1. Further work

Considering the development and evolution of power systems, which are gradually transitioning to integrated energy systems, it is imperative to develop planning models that can incorporate multiple technologies in a detailed manner and consider the uncertainties associated with the various input vectors that impact their operation. In particular, assets for the production and transport of hydrogen, such as pipelines and electrolysers, can provide flexibility for power systems with high penetration of renewables. However, long-term uncertainties associated with deploying renewable generation and transmission could significantly impact the development of this fuel.

On the other hand, since distribution networks are no longer passive and more bidirectional power exchanges with the transmission network are observed, planners must consider this paradigm shift. To do so, models must be developed that leave behind the inherent demand-side inflexibility, properly valuing investments in new flexible demand-side assets. For example, for policy design, planning models could consider the trade-off between utility-scale storage investment and distributed storage so that appropriate incentives are developed. As shown in this work, assuming that DER capacity will be available and dispatchable in the future, the presence of these assets on the demand side reduces the total investments in utility-scale assets. A step forward would be to consider investment in demand-side assets (additional DER), which is not trivial as the dynamics associated with costs, system operation, and grid constraints must be considered, given that their operation is not governed by the same principles as utility-scale assets.

Risk management is another critical aspect of power systems planning when considering multiple scenarios. If investment decisions are not appropriate, system costs can increase substantially in the face of adverse scenarios. Thus, the proposed expansion model can be tuned to include metrics associated with risk quantification, allowing a balance between expected cost minimisation and risk. It is important to mention that this has already been done in previous works. However, the specific impact of DER has not been evaluated. Likewise, scaling an expansion problem for practical analysis through a decomposition algorithm is not trivial, as substantial changes must be made to the constraints used in the master problem to define the risk measurement.

Finally, another limitation associated with planning problems is the size of the resulting optimisation models, which cover multiple years and have hard linking constraints. Although different decomposition algorithms have been able to successfully tackle this problem, as energy systems become more integrated, the size of new models grows, making it more challenging to solve and increasing computation times. This is how algorithms associated with artificial intelligence, such as physics-informed neural networks, could be a promising path to solve the MILP of long-term planning problems faster and efficiently without sacrificing temporal or spatial resolution or the number of scenarios under consideration.

Bibliography

[1] International Energy Agency, "World Energy Outlook 2022," 2022, https://www.iea.org/reports/world-energy-outlook-2022.

[2] International Energy Agency, "Unlocking the Potential of Distributed Energy Resources," 2022, https://www.iea.org/reports/unlocking-the-potential-of-distributed-energy-resources.

[3] Alvarado, D., Moreira, A., Moreno, R., and Strbac, G., "Transmission Network Investment with Distributed Energy Resources and Distributionally Robust Security," IEEE Transactions on Power Systems, vol. 34, pp. 5157–5168, 2019, doi:10.1109/TPWRS.2018.2867226.

[4] Perez-Arriaga, I. J., "The Transmission of the Future: The Impact of Distributed Energy Resources on the Network," IEEE Power and Energy Magazine, vol. 14, pp. 41–53, 2016, doi:10.1109/MPE.2016.2550398.

[5] Strbac, G., Kirschen, D., and Moreno, R., Reliability Standards for the Operation and Planning of Future Electricity Networks, vol. 1. Now Publishers, 2016, doi:10.1561/3100000001.

[6] Moreno, R., Street, A., Arroyo, J. M., and Mancarella, P., "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, 2017, doi:10.1098/rsta.2016.0305.

[7] Australian Energy Market Operator (AEMO), "Integrated System Plan For the National Electricity Market," 2022.

[8] Moya, B., Moreno, R., Püschel-Løvengreen, S., Costa, A. M., and Mancarella, P., "Uncertainty representation in investment planning of low-carbon power systems," Electric Power Systems Research, vol. 212, 2022, doi:10.1016/J.EPSR.2022.108470.

[9] Flores-Quiroz, A. and Strunz, K., "A distributed computing framework for multi-stage stochastic planning of renewable power systems with energy storage as flexibility option," Applied Energy, vol. 291, 2021, doi:10.1016/j.apenergy.2021.116736.

[10] Cigre Technical Council, Electricity Supply Systems of the Future. 2020, http://www.springer.com/series/15383.

[11] Ulbig, A. and Andersson, G., "Analyzing operational flexibility of electric power systems,"

International Journal of Electrical Power and Energy Systems, vol. 72, pp. 155–164, 2015, doi:10.1016/j.ijepes.2015.02.028.

[12] Riaz, S. and Mancarella, P., "Modelling and Characterisation of Flexibility from Distributed Energy Resources," IEEE Transactions on Power Systems, vol. 37, pp. 38–50, 2022, doi:10.1109/TPWRS.2021.3096971.

[13] International Energy Agency (IEA), "Status of Power System Transformation," 2019, https://www.iea.org/reports/status-of-power-system-transformation-2019.

[14] Burger, S., Chaves-Ávila, J. P., Batlle, C., and Pérez-Arriaga, I. J., "A review of the value of aggregators in electricity systems," Renewable and Sustainable Energy Reviews, vol. 77, pp. 395–405, 2017, doi:10.1016/j.rser.2017.04.014.

[15] Kieny, C., Berseneff, B., Hadjsaid, N., Yvon, B., and Maire, J., "On the concept and the interest of Virtual Power plant: some results from the European project FENIX," in IEEE General Meeting Power & Energy Society, IEEE, 2009.

[16] International Renewable Energy Agency (IRENA), "Aggregators: Innovation Landscape Brief," 2019, https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Feb/IRENA_Innovation_Aggregators_2019.PDF.

[17] Naughton, J., Wang, H., Riaz, S., Cantoni, M., and Mancarella, P., "Optimization of multi-energy virtual power plants for providing multiple market and local network services," Electric Power Systems Research, vol. 189, 2020, doi:10.1016/j.epsr.2020.106775.

[18] Wang, H., Riaz, S., and Mancarella, P., "Integrated techno-economic modeling, flexibility analysis, and business case assessment of an urban virtual power plant with multi-market co-optimization," Applied Energy, vol. 259, 2020, doi:10.1016/j.apenergy.2019.114142.

[19] Perez-Arriaga, I. J., "The Transmission of the Future: The Impact of Distributed Energy Resources on the Network," IEEE Power and Energy Magazine, vol. 14, pp. 41–53, 2016, doi:10.1109/MPE.2016.2550398.

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

[21] Möbius, T., Riepin, I., Müsgens, F., and van der Weijde, A. H., "Risk aversion and flexibility options in electricity markets," Energy Economics, vol. 126, p. 106767, 2023, doi:10.1016/j.eneco.2023.106767.

[22] Alvarado, D., Moreno, R., Street, A., Panteli, M., Mancarella, P., and Strbac, G., "Co-Optimizing Substation Hardening and Transmission Expansion Against Earthquakes: A Decision-Dependent Probability Approach," IEEE Transactions on Power Systems, 2023,

doi:10.1109/TPWRS.2022.3180363.

[23] Manríquez, F., Sauma, E., Aguado, J., de la Torre, S., and Contreras, J., "The impact of electric vehicle charging schemes in power system expansion planning," Applied Energy, vol. 262, 2020, doi:10.1016/j.apenergy.2020.114527.

[24] Wang, D. T., Ochoa, L. F., and Harrison, G. P., "DG impact on investment deferral: Network planning and security of supply," IEEE Transactions on Power Systems, vol. 25, pp. 1134–1141, 2010, doi:10.1109/TPWRS.2009.2036361.

[25] Piccolo, A. and Siano, P., "Evaluating the impact of network investment deferral on distributed generation expansion," IEEE Transactions on Power Systems, vol. 24, no. 3, pp. 1559–1567, 2009, doi:10.1109/TPWRS.2009.2022973.

[26] Luo, F., Zhao, J., Qiu, J., Foster, J., Peng, Y., and Dong, Z., "Assessing the transmission expansion cost with distributed generation: An australian case study," IEEE Transactions on Smart Grid, vol. 5, no. 4, pp. 1892–1904, 2014, doi:10.1109/TSG.2014.2314451.

[27] Vilaça Gomes, P. and Tome Saraiva, J., "Transmission System Planning Considering Solar Distributed Generation Penetration," in International Conference on European Electricity Market, EEM, 2017.

[28] Alvarez, E. F., Olmos, L., Ramos, A., Antoniadou-Plytaria, K., Steen, D., and Tuan, L. A., "Values and impacts of incorporating local flexibility services in transmission expansion planning," Electric Power Systems Research, vol. 212, 2022, doi:10.1016/j.epsr.2022.108480.

[29] Paredes-Vergara, M., Palma-Behnke, R., and Haas, J., "Characterizing decision making under deep uncertainty for model-based energy transitions," Renewable and Sustainable Energy Reviews, vol. 192, p. 114233, 2024, doi:10.1016/j.rser.2023.114233.

[30] Velasquez, C., Watts, D., Rudnick, H., and Bustos, C., "A Framework for Transmission Expansion Planning: A Complex Problem Clouded by Uncertainty," IEEE Power and Energy Magazine, vol. 14, pp. 20–29, 2016, doi:10.1109/MPE.2016.2547278.

[31] Mancarella, P., Püschel-Løvengreen, S., Zhang, L., and Domenech, C. B., "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.

[32] Mancarella, P., Zhang, L., and Püschel-Løvengreen, S., "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, https://www.nationalgrideso.com/document/185826/download.

[33] Püschel-Løvengreen, S., Security-constrained expansion planning of low carbon power systems. PhD thesis, The University of Melbourne, Melbourne, 2021.

[34] Ma, J., Silva, V., Belhomme, R., Kirschen, D. S., and Ochoa, L. F., “Evaluating and planning flexibility in sustainable power systems,” IEEE Transactions on Sustainable Energy, vol. 4, no. 1, pp. 200–209, 2013, doi:10.1109/TSTE.2012.2212471.

[35] Palmintier, B. S. and Webster, M. D., “Impact of Operational Flexibility on Electricity Generation Planning with Renewable and Carbon Targets,” IEEE Transactions on Sustainable Energy, vol. 7, pp. 672–684, 2016, doi:10.1109/TSTE.2015.2498640.

[36] Poncelet, K., Delarue, E., and D’haeseleer, W., “Unit commitment constraints in long-term planning models: Relevance, pitfalls and the role of assumptions on flexibility,” Applied Energy, vol. 258, 2020, doi:10.1016/j.apenergy.2019.113843.

[37] Helistö, N., Kiviluoma, J., Holttinen, H., Lara, J. D., and Hodge, B. M., “Including operational aspects in the planning of power systems with large amounts of variable generation: A review of modeling approaches,” Wiley Interdisciplinary Reviews: Energy and Environment, vol. 8, 2019, doi:10.1002/wene.341.

[38] Dvorkin, Y., Ricardo, F. B., Wang, Y., Xu, B., Kirschen, D. S., Pandžić, H., Watson, J. P., and Cesar, A. S. M., “Co-planning of investments in transmission and merchant energy storage,” IEEE Transactions on Power Systems, vol. 33, pp. 245–256, 2018, doi:10.1109/TPWRS.2017.2705187.

[39] Diaz, G., Inzunza, A., and Moreno, R., “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.

[40] Püschel-Løvengreen, S., Mhanna, S., and Mancarella, P., “Flexible planning of low-carbon power systems under deep uncertainty,” CIGRE Science and Engineering, vol. 31, 2023, https://cse.cigre.org/cse-n031/flexible-planning-of-low-carbon-power-systems-under-deep-uncertainty.html.

[41] Schwele, A., Kazempour, J., and Pinson, P., “Do unit commitment constraints affect generation expansion planning? A scalable stochastic model,” Energy Systems, vol. 11, pp. 247–282, 2020, doi:10.1007/s12667-018-00321-z.

[42] Oree, V., Sayed Hassen, S. Z., and Fleming, P. J., “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.

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

[44] Gomes, P. V. and Saraiva, J. T., “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.

[45] Gacitua, L., Gallegos, P., Henriquez-Auba, R., Lorca, Negrete-Pincetic, M., Olivares, D., Valenzuela, A., and Wenzel, G., "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.

[46] Singh, K. J., Philpott, A. B., and Wood, R. K., "Dantzig-Wolfe Decomposition for Solving Multistage Stochastic Capacity-Planning Problems," Operations Research, vol. 57, no. 5, pp. 1271–1286, 2009, doi:10.1287/opre.1080.0678.

[47] Flores-Quiroz, A., Palma-Behnke, R., Zakeri, G., and Moreno, R., "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.

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

[49] Wogrin, S., Tejada-Arango, D., Downward, A., and Philpott, A. B., "Welfare-maximizing transmission capacity expansion under uncertainty," Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, vol. 379, 2021, doi:10.1098/rsta.2019.0436.

[50] Kang, C., Zhang, N., Schaefer, C., Samarakoon, H., Mancarella, P., Lopes, C., and Reali, C., "Optimal power system planning under growing uncertainty," CIGRE Electra - C1 Power system development and economics, 2020, https://electra.cigre.org/313-december-2020/technical-brochures/optimal-power-system-planning-under-growing-uncertainty.html.

[51] Australian Energy Market Operator (AEMO), "Very Fast Frequency Response 2023 Release - Industry Go-live plan," 2023, https://www.aemo.com.au/initiatives/major-programs/nem2025-program/about-nem2025-program.

[52] Marchau, V. A. W. J., Walker, W. E., Bloemen, P. J. T. M., and Popper, S. W., Decision Making under Deep Uncertainty. 2019.

[53] Lempert, R. J., Popper, S. W., and Bankes, S. C., "Shaping the next one hundred years : new methods for quantitative, long-term policy analysis and bibliography," tech. rep., 2003.

[54] Hallegatte, S., "Strategies to adapt to an uncertain climate change," Global Environmental Change, vol. 19, no. 2, pp. 240–247, 2009, doi:10.1016/j.gloenvcha.2008.12.003.

[55] Martinez-Cesena, A. E., Real Options Theory Applied to Renewable Energy Generation Projects Planning. PhD thesis, The University of Manchester, Manchester, 2012.

[56] Püschel-Løvengreen, S., Ghazavi Dozein, M., Low, S., and Mancarella, P., "Separation event-constrained optimal power flow to enhance resilience in low-inertia power systems," Electric Power Systems Research, vol. 189, 2020, doi:10.1016/J.EPSR.2020.106678.

[57] Capitanescu, F., "Computing Cost Curves of Active Distribution Grids Aggregated Flexibility for TSO-DSO Coordination," IEEE Transactions on Power Systems, pp. 1–4, 2023, doi:10.1109/tpwrs.2023.3328156.

[58] Schachter, J. A. and Mancarella, P., "Demand Response Contracts as Real Options: A Probabilistic Evaluation Framework under Short-Term and Long-Term Uncertainties," IEEE Transactions on Smart Grid, vol. 7, pp. 868–878, 2016, doi:10.1109/TSG.2015.2405673.

[59] Zhang, L., Capuder, T., and Mancarella, P., "Unified Unit Commitment Formulation and Fast Multi-Service LP Model for Flexibility Evaluation in Sustainable Power Systems," IEEE Transactions on Sustainable Energy, vol. 7, pp. 658–671, 2016, doi:10.1109/TSTE.2015.2497411.

[60] Diaz, G., Munoz, F. D., and Moreno, R., "Equilibrium Analysis of a Tax on Carbon Emissions with Pass-through Restrictions and Side-payment Rules," The Energy Journal, vol. 41, 2020, doi:10.5547/01956574.41.2.gdia.

[61] Carrión, M. and Arroyo, J. M., "A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem," IEEE Transactions on Power Systems, vol. 21, pp. 1371–1378, 2006, doi:10.1109/TPWRS.2006.876672.

[62] Vanderbeck, F., "Implementing Mixed Integer Column Generation," in Column Generation, pp. 331–358, Springer, 2005, doi:http://dx.doi.org/10.1007/0-387-25486-2{_}12.

[63] Australian Energy Market Operator, "Inputs, Assumptions and Scenarios Report," 2021, https://aemo.com.au/en/energy-systems/major-publications/integrated-system-plan-isp/2022-integrated-system-plan-isp/2022-isp-inputs-assumptions-and-scenarios.

[64] Püschel-Løvengreen, S., Mhanna, S., Apablaza, P., and Mancarella, P., "Assessing flexibility, risk, and resilience in low-carbon power system planning under deep uncertainty," 2023, https://www.csiro.au/-/media/EF/Files/GPST-Roadmap/Final-Reports/Topic-4-GPST-Stage-2.pdf.

[65] Poncelet, K., Hoschle, H., Delarue, E., Virag, A., and Drhaeseleer, W., "Selecting representative days for capturing the implications of integrating intermittent renewables in generation expansion planning problems," IEEE Transactions on Power Systems, vol. 32, pp. 1936–1948, 2017, doi:10.1109/TPWRS.2016.2596803.

[66] Nahmmacher, P., Schmid, E., Hirth, L., and Knopf, B., "Carpe diem: A novel approach to select representative days for long-term power system modeling," Energy, vol. 112, pp. 430–442, 2016, doi:10.1016/j.energy.2016.06.081.

[67] Hsu, C.-C. and Sandford, B. A., "The Delphi Technique: Making Sense of Consensus," Prac-

tical Assessment, Research, and Evaluation, vol. 12, p. 10, 2007, doi:10.7275/pdz9-th90.

Annexes

Annex A. 2022 Integrated System Plan scenarios

- **Slow Change:** this scenario considers a challenging economic environment after the COVID-19 pandemic, a higher risk of industrial load closures, and slower actions to reach net-zero emissions. Consumers continue to manage their energy needs through DER, mainly distributed PV. However, in this scenario, the decarbonisation targets of Australia's Emissions Reduction Plan are not reached.

- **Progressive Change:** the net zero emissions 2050 target is progressively reached. This scenario delivers a net zero emission economy, with deep cuts in emissions across the economy from the 2040s. The trends in this scenario continue with consumer DER investment and technology cost reductions. Commercial alternatives to the heavy emissions industry emerge, paving the way for the system's decarbonisation and electrification, doubling the total installed capacity of the NEM. EVs have become prevalent, and consumers have switched to electrification alternatives for heating and cooling.

- **Step Change:** a rapid consumer-led transformation of the energy sector is projected in this scenario, modelling a much faster commitment to reach the net zero policy targets. Compared to *Progressive Change*, *Step Change* shows a fast-paced transition from fossil fuel to renewable energy in the NEM. On top of the *Progressive Change* assumptions, there is a Step Change in global policy commitments, supported by rapidly decreasing energy production costs, including consumer devices. Digitalisation increases visibility and controllability for demand management and grid flexibility. By 2050, most consumers will rely on electricity for heating and transport.

- **Hydrogen Superpower:** significant technological breakthroughs due to the integration of energy systems. *Hydrogen Superpower* quadruples the NEM energy consumption to support a hydrogen export industry. The technology transforms transport and domestic manufacturing. Renewable energy exports become a significant Australian export, retaining the country's place as a global energy resource.

In addition to the data associated with the scenarios, AEMO conducts a Delphi panel[1] with multiple experts and stakeholders in the energy sector. Through this panel, the expected weights of the scenarios are obtained [7], which translates into the probability of occurrence of each of them, ρ_s, shown in Table A.1. These values are used in the ISP methodology to evaluate and weigh the net market benefits of each candidate development plan (CDP) to determine the Optimal Development Plan (ODP), in which the portfolio that minimises risks and costs is obtained according to the methodology used by the system operator.

Table A.1: Probabilities assigned for the 2022 ISP scenarios.

Scenario s	**Probability** ρ_s
Slow Change	0.04
Progressive Change	0.29
Step Change	0.5
Hydrogen Superpower	0.17

Through the scenarios presented above, the methodology of the ISP aims to find the least cost development path for each scenario independently. Each deterministic least-cost development path is determined using a generation and transmission expansion model, resulting in hourly dispatch outcomes that are tested for security criteria (fault levels, dynamics, voltage compliance, etc.) using electromagnetic transient analysis software. Then, those results determine the least regret development path across all scenarios.

[1] The Delphi technique is a method for gathering data from respondents within their domain of expertise. The technique is designed as a group communication process that aims to achieve a convergence of opinion on a specific real-world issue [67].

Annex B. Existing storage assets

Table B.1: Parameters of existing utility-scale storage units for the year 2022.

#	Name	Tech	Depth	Capacity [MW] 2022	Capacity [MW] 2037	Bus	Round-trip efficiency	Duration [hr]
1	Deep QLD	PS	Deep	0	1300	SQ	72%	24.0
2	Medium QLD	BESS	Medium	570	1600	SQ	84%	10.0
3	Shallow QLD	BESS	Shallow	100	100	SQ	84%	1.5
4	Deep NSW	PS	Deep	160	660	CNSW	72%	37.8
5	Medium NSW	BESS	Medium	80	2100	CNSW	84%	7.8
6	Shallow NSW	BESS	Shallow	50	50	CNSW	84%	1.5
7	Snowy 2.0	PS	Deep	0	2040	CNSW	72%	175.0
8	Deep VIC	PS	Deep	0	720	VIC	72%	24.0
9	Medium VIC	BESS	Medium	0	580	VIC	84%	8.0
10	Shallow VIC	BESS	Shallow	124	380	VIC	84%	1.5
11	Medium SA	BESS	Medium	0	3100	SA	84%	8.0
12	Shallow SA	BESS	Shallow	473	470	SA	84%	1.1
13	Deep TAS	PS	Deep	0	500	TAS	72%	22.0
14	Medium TAS	BESS	Medium	0	0	TAS	84%	–

Annex C. Candidate transmission investment projects

Table C.1: Parameters of candidate transmission lines.

#	Bus A	Bus B	Name	Transfer limits [MW]		Inv. Cost
				A to B	B to A	[M$/MW]
13	CNQ	GG	CNQ-GG Option 1	500	550	0.74
14	SQ	CNQ	SQ-CNQ Option 1	900	900	0.53
15	SQ	CNQ	SQ-CNQ Option 2	300	0	0.18
17	CNQ	SQ	CNQ-SQ Option 4	1500	1500	1.08
18	NNSW	SQ	NNSW-SQ Option 1	1080	910	1.16
19	NNSW	SQ	NNSW-SQ Option 2	800	550	0.48
21	NNSW	SQ	NNSW-SQ Option 4	2000	1800	1.56
22	CNSW	NNSW	CNSW-NNSW Option 1	1660	2035	1.76
23	CNSW	NNSW	CNSW-NNSW Option 2	535	710	2.72
24	CNSW	NNSW	CNSW-NNSW Option 3	470	585	2.40
25	CNSW	NNSW	CNSW-NNSW Option 4	535	710	2.67
26	CNSW	NNSW	CNSW-NNSW Option 5	470	585	0.87
27	CNSW	NNSW	CNSW-NNSW Option 6	1800	2190	0.77
28	CNSW	NNSW	CNSW-NNSW Option 6A	1270	880	0.18
29	CNSW	NNSW	CNSW-NNSW Option 6B	2750	2750	0.45
30	CNSW	NNSW	CNSW-NNSW Option 7	1590	1470	0.56
32	CNSW	NNSW	CNSW-NNSW Option 9	2000	1750	1.06
33	CNSW	NNSW	CNSW-NNSW Option 10	2000	1750	1.15
34	CNSW	SNW	CNSW-SNW Option 1	0	5000	0.18
35	CNSW	SNW	CNSW-SNW Option 2	0	4500	0.50
36	CNSW	SNW	CNSW-SNW Option 3a	0	600	3.76
37	CNSW	SNW	CNSW-SNW Option 3b	0	1100	0.80
38	CNSW	SNW	H-Newcastle	5000	5000	0.31
39	CNSW	SNW	H-Dapto	5000	5000	0.24
40	SNSW	CNSW	SNSW-CNSW Option 1	2200	2200	1.51
41	SNSW	CNSW	SNSW-CNSW Option 2	2000	2000	0.48
42	SNSW	CNSW	SNSW-CNSW Option 3	2000	2000	1.02
43	VIC	SNSW	VIC-SNSW Option 1 - VNI West	1800	1930	1.40
44	VIC	SNSW	VIC-SNSW Option 2 - VNI West	1800	1930	1.52
45	VIC	SNSW	VIC-SNSW Option 6A	1800	1930	1.20
46	VIC	SNSW	VIC-SNSW Option 6	1500	2000	1.16
47	VIC	SNSW	VIC-SNSW Option 7	2000	2000	1.26
48	TAS	VIC	TAS-VIC Option 1	750	750	3.17
49	TAS	VIC	TAS-VIC Option 2	750	750	1.87

Annex D. Representative periods

Node	Scenario	Start	End	Node	Scenario	Start	End
1	Step Change	2022-08-08 00:00:00	2022-08-14 23:00:00	17	Step Change	2037-03-21 00:00:00	2037-03-27 23:00:00
1	Step Change	2022-09-12 00:00:00	2022-09-18 23:00:00	17	Step Change	2037-12-12 00:00:00	2037-12-18 23:00:00
1	Step Change	2022-08-29 00:00:00	2022-09-04 23:00:00	17	Step Change	2037-11-21 00:00:00	2037-11-27 23:00:00
1	Step Change	2022-05-02 00:00:00	2022-05-08 23:00:00	17	Step Change	2037-11-28 00:00:00	2037-12-04 23:00:00
1	Step Change	2022-11-14 00:00:00	2022-11-20 23:00:00	17	Step Change	2037-12-19 00:00:00	2037-12-25 23:00:00
2	Slow Change	2027-11-14 00:00:00	2027-11-20 23:00:00	18	Progressive Change	2037-01-31 00:00:00	2037-02-06 23:00:00
2	Slow Change	2027-04-04 00:00:00	2027-04-10 23:00:00	18	Progressive Change	2037-09-26 00:00:00	2037-10-02 23:00:00
2	Slow Change	2027-07-18 00:00:00	2027-07-24 23:00:00	18	Progressive Change	2037-10-10 00:00:00	2037-10-16 23:00:00
2	Slow Change	2027-10-17 00:00:00	2027-10-23 23:00:00	18	Progressive Change	2037-06-13 00:00:00	2037-06-19 23:00:00
2	Slow Change	2027-10-17 00:00:00	2027-10-23 23:00:00	18	Progressive Change	2037-04-11 00:00:00	2037-04-17 23:00:00
3	Progressive Change	2027-07-04 00:00:00	2027-07-10 23:00:00	19	Step Change	2037-03-21 00:00:00	2037-03-27 23:00:00
3	Progressive Change	2027-06-06 00:00:00	2027-06-12 23:00:00	19	Step Change	2037-12-12 00:00:00	2037-12-18 23:00:00
3	Progressive Change	2027-08-08 00:00:00	2027-08-14 23:00:00	19	Step Change	2037-11-21 00:00:00	2037-11-27 23:00:00
3	Progressive Change	2027-06-06 00:00:00	2027-06-12 23:00:00	19	Step Change	2037-11-28 00:00:00	2037-12-04 23:00:00
3	Progressive Change	2027-02-28 00:00:00	2027-03-06 23:00:00	19	Step Change	2037-12-19 00:00:00	2037-12-25 23:00:00
4	Step Change	2027-09-12 00:00:00	2027-09-18 23:00:00	20	Hydrogen Superpower	2037-06-20 00:00:00	2037-06-26 23:00:00
4	Step Change	2027-05-16 00:00:00	2027-05-22 23:00:00	20	Hydrogen Superpower	2037-07-11 00:00:00	2037-07-17 23:00:00
4	Step Change	2027-11-14 00:00:00	2027-11-20 23:00:00	20	Hydrogen Superpower	2037-01-24 00:00:00	2037-01-30 23:00:00
4	Step Change	2027-03-14 00:00:00	2027-03-20 23:00:00	20	Hydrogen Superpower	2037-09-05 00:00:00	2037-09-11 23:00:00
4	Step Change	2027-06-06 00:00:00	2027-06-12 23:00:00	20	Hydrogen Superpower	2037-08-15 00:00:00	2037-08-21 23:00:00
5	Hydrogen Superpower	2027-09-19 00:00:00	2027-09-25 23:00:00	21	Step Change	2037-03-21 00:00:00	2037-03-27 23:00:00
5	Hydrogen Superpower	2027-02-28 00:00:00	2027-03-06 23:00:00	21	Step Change	2037-12-12 00:00:00	2037-12-18 23:00:00
5	Hydrogen Superpower	2027-02-07 00:00:00	2027-02-13 23:00:00	21	Step Change	2037-11-21 00:00:00	2037-11-27 23:00:00
5	Hydrogen Superpower	2027-03-14 00:00:00	2027-03-20 23:00:00	21	Step Change	2037-11-28 00:00:00	2037-12-04 23:00:00
5	Hydrogen Superpower	2027-02-21 00:00:00	2027-02-27 23:00:00	21	Step Change	2037-12-19 00:00:00	2037-12-25 23:00:00
6	Slow Change	2032-03-06 00:00:00	2032-03-12 23:00:00	22	Hydrogen Superpower	2037-06-20 00:00:00	2037-06-26 23:00:00
6	Slow Change	2032-03-20 00:00:00	2032-03-26 23:00:00	22	Hydrogen Superpower	2037-07-11 00:00:00	2037-07-17 23:00:00
6	Slow Change	2032-07-24 00:00:00	2032-07-30 23:00:00	22	Hydrogen Superpower	2037-01-24 00:00:00	2037-01-30 23:00:00
6	Slow Change	2032-11-27 00:00:00	2032-12-03 23:00:00	22	Hydrogen Superpower	2037-09-05 00:00:00	2037-09-11 23:00:00
6	Slow Change	2032-03-27 00:00:00	2032-04-02 23:00:00	22	Hydrogen Superpower	2037-08-15 00:00:00	2037-08-21 23:00:00
7	Progressive Change	2032-10-09 00:00:00	2032-10-15 23:00:00	23	Progressive Change	2037-01-31 00:00:00	2037-02-06 23:00:00
7	Progressive Change	2032-08-07 00:00:00	2032-08-13 23:00:00	23	Progressive Change	2037-09-26 00:00:00	2037-10-02 23:00:00
7	Progressive Change	2032-09-11 00:00:00	2032-09-17 23:00:00	23	Progressive Change	2037-10-10 00:00:00	2037-10-16 23:00:00
7	Progressive Change	2032-06-19 00:00:00	2032-06-25 23:00:00	23	Progressive Change	2037-06-13 00:00:00	2037-06-19 23:00:00
7	Progressive Change	2032-09-25 00:00:00	2032-10-01 23:00:00	23	Progressive Change	2037-04-11 00:00:00	2037-04-17 23:00:00
8	Step Change	2032-03-27 00:00:00	2032-04-02 23:00:00	24	Step Change	2037-03-21 00:00:00	2037-03-27 23:00:00
8	Step Change	2032-07-17 00:00:00	2032-07-23 23:00:00	24	Step Change	2037-12-12 00:00:00	2037-12-18 23:00:00
8	Step Change	2032-10-09 00:00:00	2032-10-15 23:00:00	24	Step Change	2037-11-21 00:00:00	2037-11-27 23:00:00
8	Step Change	2032-05-15 00:00:00	2032-05-21 23:00:00	24	Step Change	2037-11-28 00:00:00	2037-12-04 23:00:00
8	Step Change	2032-08-28 00:00:00	2032-09-03 23:00:00	24	Step Change	2037-12-19 00:00:00	2037-12-25 23:00:00
9	Progressive Change	2032-10-09 00:00:00	2032-10-15 23:00:00	25	Hydrogen Superpower	2037-06-20 00:00:00	2037-06-26 23:00:00
9	Progressive Change	2032-08-07 00:00:00	2032-08-13 23:00:00	25	Hydrogen Superpower	2037-07-11 00:00:00	2037-07-17 23:00:00
9	Progressive Change	2032-09-11 00:00:00	2032-09-17 23:00:00	25	Hydrogen Superpower	2037-01-24 00:00:00	2037-01-30 23:00:00
9	Progressive Change	2032-06-19 00:00:00	2032-06-25 23:00:00	25	Hydrogen Superpower	2037-09-05 00:00:00	2037-09-11 23:00:00
9	Progressive Change	2032-09-25 00:00:00	2032-10-01 23:00:00	25	Hydrogen Superpower	2037-08-15 00:00:00	2037-08-21 23:00:00
10	Step Change	2032-03-27 00:00:00	2032-04-02 23:00:00	26	Step Change	2037-03-21 00:00:00	2037-03-27 23:00:00
10	Step Change	2032-07-17 00:00:00	2032-07-23 23:00:00	26	Step Change	2037-12-12 00:00:00	2037-12-18 23:00:00
10	Step Change	2032-10-09 00:00:00	2032-10-15 23:00:00	26	Step Change	2037-11-21 00:00:00	2037-11-27 23:00:00
10	Step Change	2032-05-15 00:00:00	2032-05-21 23:00:00	26	Step Change	2037-11-28 00:00:00	2037-12-04 23:00:00
10	Step Change	2032-08-28 00:00:00	2032-09-03 23:00:00	26	Step Change	2037-12-19 00:00:00	2037-12-25 23:00:00
11	Hydrogen Superpower	2032-02-14 00:00:00	2032-02-20 23:00:00	27	Hydrogen Superpower	2037-06-20 00:00:00	2037-06-26 23:00:00
11	Hydrogen Superpower	2032-11-27 00:00:00	2032-12-03 23:00:00	27	Hydrogen Superpower	2037-07-11 00:00:00	2037-07-17 23:00:00
11	Hydrogen Superpower	2032-09-18 00:00:00	2032-09-24 23:00:00	27	Hydrogen Superpower	2037-01-24 00:00:00	2037-01-30 23:00:00
11	Hydrogen Superpower	2032-11-27 00:00:00	2032-12-03 23:00:00	27	Hydrogen Superpower	2037-09-05 00:00:00	2037-09-11 23:00:00
11	Hydrogen Superpower	2032-05-22 00:00:00	2032-05-28 23:00:00	27	Hydrogen Superpower	2037-08-15 00:00:00	2037-08-21 23:00:00
12	Step Change	2032-03-27 00:00:00	2032-04-02 23:00:00	28	Hydrogen Superpower	2037-06-20 00:00:00	2037-06-26 23:00:00
12	Step Change	2032-07-17 00:00:00	2032-07-23 23:00:00	28	Hydrogen Superpower	2037-07-11 00:00:00	2037-07-17 23:00:00
12	Step Change	2032-10-09 00:00:00	2032-10-15 23:00:00	28	Hydrogen Superpower	2037-01-24 00:00:00	2037-01-30 23:00:00
12	Step Change	2032-05-15 00:00:00	2032-05-21 23:00:00	28	Hydrogen Superpower	2037-09-05 00:00:00	2037-09-11 23:00:00
12	Step Change	2032-08-28 00:00:00	2032-09-03 23:00:00	28	Hydrogen Superpower	2037-08-15 00:00:00	2037-08-21 23:00:00
13	Hydrogen Superpower	2032-02-14 00:00:00	2032-02-20 23:00:00	29	Step Change	2037-03-21 00:00:00	2037-03-27 23:00:00
13	Hydrogen Superpower	2032-11-27 00:00:00	2032-12-03 23:00:00	29	Step Change	2037-12-12 00:00:00	2037-12-18 23:00:00
13	Hydrogen Superpower	2032-09-18 00:00:00	2032-09-24 23:00:00	29	Step Change	2037-11-21 00:00:00	2037-11-27 23:00:00
13	Hydrogen Superpower	2032-11-27 00:00:00	2032-12-03 23:00:00	29	Step Change	2037-11-28 00:00:00	2037-12-04 23:00:00
13	Hydrogen Superpower	2032-05-22 00:00:00	2032-05-28 23:00:00	29	Step Change	2037-12-19 00:00:00	2037-12-25 23:00:00
14	Hydrogen Superpower	2032-02-14 00:00:00	2032-02-20 23:00:00	30	Hydrogen Superpower	2037-06-20 00:00:00	2037-06-26 23:00:00
14	Hydrogen Superpower	2032-11-27 00:00:00	2032-12-03 23:00:00	30	Hydrogen Superpower	2037-07-11 00:00:00	2037-07-17 23:00:00
14	Hydrogen Superpower	2032-09-18 00:00:00	2032-09-24 23:00:00	30	Hydrogen Superpower	2037-01-24 00:00:00	2037-01-30 23:00:00
14	Hydrogen Superpower	2032-11-27 00:00:00	2032-12-03 23:00:00	30	Hydrogen Superpower	2037-09-05 00:00:00	2037-09-11 23:00:00
14	Hydrogen Superpower	2032-05-22 00:00:00	2032-05-28 23:00:00	30	Hydrogen Superpower	2037-08-15 00:00:00	2037-08-21 23:00:00
15	Slow Change	2037-09-26 00:00:00	2037-10-02 23:00:00	31	Hydrogen Superpower	2037-06-20 00:00:00	2037-06-26 23:00:00
15	Slow Change	2037-10-24 00:00:00	2037-10-30 23:00:00	31	Hydrogen Superpower	2037-07-11 00:00:00	2037-07-17 23:00:00
15	Slow Change	2037-12-19 00:00:00	2037-12-25 23:00:00	31	Hydrogen Superpower	2037-01-24 00:00:00	2037-01-30 23:00:00
15	Slow Change	2037-09-26 00:00:00	2037-10-02 23:00:00	31	Hydrogen Superpower	2037-09-05 00:00:00	2037-09-11 23:00:00
15	Slow Change	2037-08-15 00:00:00	2037-08-21 23:00:00	31	Hydrogen Superpower	2037-08-15 00:00:00	2037-08-21 23:00:00
16	Progressive Change	2037-01-31 00:00:00	2037-02-06 23:00:00	32	Hydrogen Superpower	2037-06-20 00:00:00	2037-06-26 23:00:00
16	Progressive Change	2037-09-26 00:00:00	2037-10-02 23:00:00	32	Hydrogen Superpower	2037-07-11 00:00:00	2037-07-17 23:00:00
16	Progressive Change	2037-10-10 00:00:00	2037-10-16 23:00:00	32	Hydrogen Superpower	2037-01-24 00:00:00	2037-01-30 23:00:00
16	Progressive Change	2037-06-13 00:00:00	2037-06-19 23:00:00	32	Hydrogen Superpower	2037-09-05 00:00:00	2037-09-11 23:00:00
16	Progressive Change	2037-04-11 00:00:00	2037-04-17 23:00:00	32	Hydrogen Superpower	2037-08-15 00:00:00	2037-08-21 23:00:00

Annex E. Description of the scenario tree

Table E.1: Description of the scenario tree.

# Scenario	Stage #2 - 2027	Stage #3 - 2032	Stage #4 - 2037	Scenario probability ρ_s
1	Slow Change	Slow Change	Slow Change	0.0018
2	Slow Change	Slow Change	Progressive Change	0.0024
3	Slow Change	Slow Change	Step Change	0.0042
4	Slow Change	Progressive Change	Progressive Change	0.0038
5	Slow Change	Progressive Change	Step Change	0.0058
6	Slow Change	Progressive Change	Hydrogen Superpower	0.002
7	Slow Change	Step Change	Step Change	0.0166
8	Slow Change	Step Change	Hydrogen Superpower	0.0034
9	Progressive Change	Progressive Change	Progressive Change	0.0316
10	Progressive Change	Progressive Change	Step Change	0.0479
11	Progressive Change	Progressive Change	Hydrogen Superpower	0.0163
12	Progressive Change	Step Change	Step Change	0.1204
13	Progressive Change	Step Change	Hydrogen Superpower	0.0247
14	Progressive Change	Hydrogen Superpower	Hydrogen Superpower	0.0493
15	Step Change	Step Change	Step Change	0.3445
16	Step Change	Step Change	Hydrogen Superpower	0.0706
17	Step Change	Hydrogen Superpower	Hydrogen Superpower	0.085
18	Hydrogen Superpower	Hydrogen Superpower	Hydrogen Superpower	0.17

Annex F. Techno-economic analysis of investment portfolios

This appendix provides an analysis of the investment portfolios for the four case studies carried conducted in this thesis. The section focuses on explaining and understanding how the controllability of DER and investment in energy storage, along with their interaction, impacts the investment decisions made by the model. Therefore, this section aims to comprehend the impact of flexible technologies on the resulting investment portfolios while considering the different modelling and investment assumptions.

Base case - Only investment in transmission / non-controllable DER

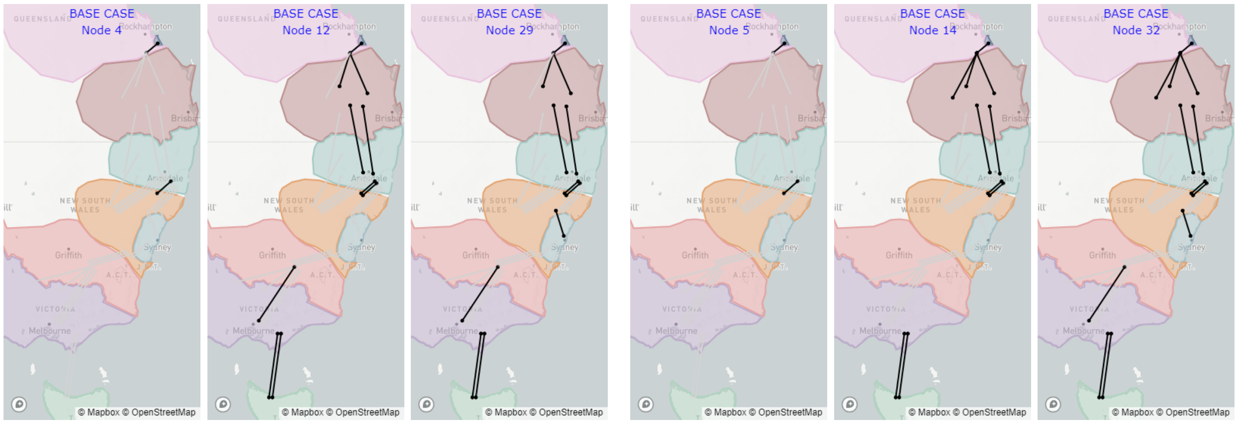
The optimal portfolio of transmission lines for the base case, using the stochastic model, is presented in Table F.1 and further detailed for *Step Change* and *Hydrogen Superpower* scenarios in Figure F.1. The results indicate that nine links need to be constructed in all scenarios, emphasising the necessity for significant transmission expansions when there is no option to invest in storage, and DER are not controllable.

Table F.1: Optimal investment portfolio - base case.

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

Most investments reinforce the internal connection within the northern states (QLD and NSW). Four of the selected options (lines 13, 14, 15 and 17) reinforce inner QLD, while three reinforce inner NSW (lines 27, 28 and 34), adding considerable intrastate transmission capacity, attributable to the need to displace higher amounts of renewable energy to the load centres from production zones and leverage the large scale storage within each state. For example, the CNSW-SNW Option 1 deploys, by 2037, 5 GW of transmission between CSNW and SNW (the second largest load centre in the system). This is explained by the availability of *Snowy 2.0*, a long-duration storage asset, in CNSW in the late 2020s, providing significant arbitrage capabilities to the system.

Regarding interstate investments, the model decides that reinforcements in the QLD-NSW (lines 18 and 19), NSW-VIC (line 45) and TAS-VIC (lines 48 and 49) corridors are mandatory, as their construction is required in all the scenarios. Remarkably, all the interstate investments add approximately 1.5 GW of transmission capacity each. This underscores that to have the most optimal operation possible when there is no controllability of DER and no additional investment in storage, the system requires large amounts of reinforcement of its interconnectors and intrastate transmission systems.



(a) *Step Change* - Scenario 15 (b) *Hydrogen Superpower* - Scenario 18

Figure F.1: Deployment of investment portfolios - base case.

Case #1 - Investment in transmission and BESS / non-controllable DER

Table F.2 presents the optimal investment portfolio in transmission lines when the model can invest in transmission lines and utility-scale energy storage, but DER are not controllable. In this case, the number of links built in all the scenarios is reduced from nine to six.

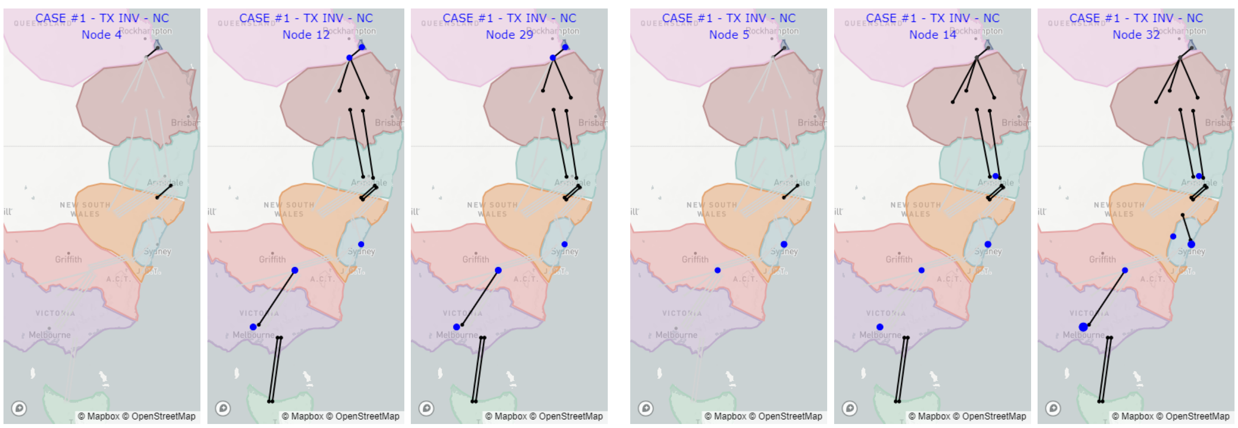
Table F.2: Optimal investment portfolio - case #1.

Line	Line ID	Region A	Region B	Rating [MW] A to B	Rating [MW] B to A	Year asset becomes operational (Scenario)
CNQ-GG Option 1	13	CNQ	GG	500	550	2027 (All)
SQ-CNQ Option 1	14	SQ	CNQ	900	900	2032 (9-18) / 2037 (4-8)
SQ-CNQ Option 2	15	SQ	CNQ	300	0	2032 (9-18) / 2037 (4-8)
CNQ-SQ Option 4	17	CNQ	SQ	1500	1500	2032 (18) / 2037 (14, 17)
NNSW–SQ Option 1	18	NNSW	SQ	1080	910	2032 (15-18) / 2037 (4-8, 12-14)
NNSW–SQ Option 2	19	NNSW	SQ	800	550	2032 (15-18) / 2037 (4-8, 12-14)
CNSW-NNSW Option 6	27	CNSW	NNSW	1800	2190	2027 (All)
CNSW-NNSW Option 6A	28	CNSW	NNSW	1270	880	2032 (All)
CNSW-SNW Option 1	34	CNSW	SNW	0	5000	2037 (18)
VIC-SNSW Option 6A	45	VIC	SNSW	1800	1930	2032 (1-17) / 2037 (18)
TAS-VIC Option 1	48	TAS	VIC	750	750	2032 (All)
TAS-VIC Option 2	49	TAS	VIC	750	750	2032 (All)

It is observed that the model continues to internally reinforce QLD but in fewer scenarios. For example, the SQ-CNQ Option 2 goes from being built in all scenarios in 2032 in the base case to being built only in scenarios 9-18 in 2032 and delayed to 2037 in scenarios 4 to 8. In contrast, in New South Wales (NSW), two links (lines 27 and 28) that provide 3 GW of intrastate transmission capacity continue to follow the same development path across all scenarios. This underscores the fact that this state requires reinforcements in its transmission system, which investments in utility-scale storage cannot replace.

Moreover, the southern states, VIC and TAS, are also being reinforced through the VIC-SNSW Option 6A and the two TAS-VIC corridors. This highlights that, even though storage might be an investment option, the system still relies on transmission investment to transport renewable energy from the northern states of (QLD and NSW) to the southern states.

Figure F.2 illustrates the deployment pathway of the portfolios resulting from the *Step Change* and *Hydrogen Superpower* scenarios in the base case. The figure reveals that the transmission investments are almost the same (excepting the CNSW-SNW Option 1) as the ones obtained in the base case (Figure F.1). In particular, the transmission system's backbone is reinforced following the same pattern. Additionally, there is an increase in energy storage investment (blue dots), demonstrating that BESS serve more as a complement to transmission than as a supplement in the most probable scenarios. Thus, new energy storage helps to reduce costs, complementing the transmission system rather than replacing line investments.



(a) *Step Change* - Scenario 15

(b) *Hydrogen Superpower* - Scenario 18

Figure F.2: Deployment of investment portfolios - case #1.

Case #2 - Only investment in transmission / controllable DER

Table F.3 shows the resulting investments portfolio for the case #2. In this case, the model can only invest in transmission options and assumes DER are controllable. The deployment of only three projects is common for all the scenarios compared to the nine projects observed in the base case. This highlights the ability of DER to provide operational flexibility in the long term, enabling the modification of transmission investment portfolios and reducing the need for mandatory network expansions.

For this case, most transmission investments that are no longer common to all scenarios are still required in scenarios 9 through 18. These are governed mainly by *Step Change* and *Hydrogen Superpower*, which have the most significant increases in demand and deployment of solar and wind generation, justifying that reinforcement of transmission corridors is still required to move

Table F.3: Optimal investment portfolio - case #2.

Line	Line ID	Region A	Region B	Rating [MW] A to B	Rating [MW] B to A	Year asset becomes operational (Scenario)
CNQ-GG Option 1	13	CNQ	GG	500	550	2027 (All)
SQ-CNQ Option 1	14	SQ	CNQ	900	900	2032 (9-18)
SQ-CNQ Option 2	15	SQ	CNQ	300	0	2032 (9-18) / 2037 (4-8)
NNSW–SQ Option 1	18	NNSW	SQ	1080	910	2032 (9-18) / 2037 (4-8)
NNSW–SQ Option 2	19	NNSW	SQ	800	550	2032 (9-18) / 2037 (4-8)
CNSW-NNSW Option 6	27	CNSW	NNSW	1800	2190	2032 (9-18)
CNSW-NNSW Option 6A	28	CNSW	NNSW	1270	880	2032 (9-18)
CNSW-NNSW Option 6B	29	CNSW	NNSW	2750	2750	2037 (14)
CNSW-SNW Option 1	34	CNSW	SNW	0	5000	2037 (18)
H-Dapto	39	CNSW	SNW	5000	5000	2037 (17)
VIC-SNSW Option 2 - VNI West	44	VIC	SNSW	1800	1930	2037 (18)
VIC-SNSW Option 6A	45	VIC	SNSW	1800	1930	2032 (1-17)
VIC-SNSW Option 6	46	VIC	SNSW	1500	2000	2037 (18)
TAS-VIC Option 1	48	TAS	VIC	750	750	2032 (All)
TAS-VIC Option 2	49	TAS	VIC	750	750	2032 (All)

large blocks of renewable energy within and between states.

CNQ-SQ Option 4 (line 17) is no longer an asset being built. This is relevant since it demonstrates that some intrastate reinforcements with low capacity (300 MW) can be discarded if DER are controllable. A similar situation is observed for line 18, reinforcing the interstate connection between QLD and NSW. This project is only deployed in the scenarios with the most significant demand increases (*Step Change* and *Hydrogen Superpower*). Furthermore, in some of these scenarios, the construction of this line is delayed until 2037, underscoring the ability of DER to reduce reliance on some transmission corridors.

Similarly, lines 27 and 28, which reinforce NSW internally, are no longer built in all scenarios, compared to the base case, and are only deployed in scenarios 9 to 18. On the other hand, the CNSW-SNW link is only reinforced by 2037 in the scenarios dominated by *Hydrogen Superpower* (17 and 18). This indicates that the arbitrage capacity of the Snowy 2.0 long-duration storage located in CNSW is necessary to meet the high demand projected in this scenario, given the massive production of green hydrogen.

Another important point to mention regarding the enabling of DER controllability is observed in the VIC-NSW interconnection. In the previous two cases, the VIC-SNSW Option 6A is deployed in 2032 for the eighteen scenarios. In this case, the same pattern is repeated for scenarios 1 to 17. In scenario 18, *Hydrogen Superpower*, this line is not built in 2032. This is explained by the fact that greater flexibility from DER can delay certain investments. Then, in 2037, for this scenario, this link is doubly reinforced by the VIC-SNSW Option 6 and VNI West, adding 3.5 GW of transmission. This late reinforcement is justified by the high demand that this scenario projects towards 2037 in VIC (a peak of 13 GW in summer). Finally, the TAS-VIC double link shows the same double reinforcement as in the previous cases.

Case #3 - Investment in transmission and BESS / controllable DER

Table F.4 displays the investment portfolio for case #3, where DER are controllable, and the model can invest in storage and transmission. Similar to case #2, three links (CNQ-GG, NNSW-SQ, and TAS-VIC) are reinforced in all scenarios. Interestingly, the model's key reinforcement decisions follow the same pattern, regardless of whether it invests in storage. This reinforces the fact that storage expansion is complementary to transmission.

However, DER controllability does impact transmission network expansion decisions. This is because energy storage deployment is faster than other technologies and can be installed after uncertainties are revealed in each scenario (BESS have no lead time). On the other hand, the deployment of DER is part of the uncertainties the model deals with, so it must consider them in advance when making transmission expansion decisions. For instance, if a significant deployment of DER is expected (e.g. as in *Step Change*), the model may postpone or discard building certain transmission assets.

Table F.4: Optimal investment portfolio - case #3.

Line	Line ID	Region A	Region B	Rating [MW] A to B	Rating [MW] B to A	Year asset becomes operational (Scenario)
CNQ-GG Option 1	13	CNQ	GG	500	550	2027 (All)
SQ-CNQ Option 1	14	SQ	CNQ	900	900	2032 (9-18)
SQ-CNQ Option 2	15	SQ	CNQ	300	0	2032 (9-18) / 2037 (4-8)
NNSW–SQ Option 1	18	NNSW	SQ	1080	910	2032 (15-18) / 2037 (9-14)
NNSW–SQ Option 2	19	NNSW	SQ	800	550	2032 (18) / 2037 (9-11, 14-17)
CNSW-NNSW Option 7	30	NNSW	SQ	1590	1470	2027 (All)
VIC-SNSW Option 1 - VNI West	43	VIC	SNSW	1800	1930	2032 (1-8)
VIC-SNSW Option 6A	45	VIC	SNSW	1800	1930	2032 (9-17) / 2037 (18)
TAS-VIC Option 1	48	TAS	VIC	750	750	2032 (All)
TAS-VIC Option 2	49	TAS	VIC	750	750	2032 (1-8, 18) / 2037 (14, 17)

In case #2, the inclusion of DER already deferred and delayed some transmission expansions for specific projects. However, by combining controllable DER with investment in energy storage, the CNSW-NNSW link shows a significant change in the project that reinforces it. In the previous three cases, the reinforcement portfolio consisted of up to three options: CNSW-NNSW Option 6, 6A, and 6B, reaching 3 GW installed in some scenarios. In contrast, in this case, those three options are replaced only by CNSW-NNSW Option 7 (1.6 GW), which is deployed in 2027 for all scenarios. This provides greater certainty to the planner since the investment portfolio ends up being more robust, with only one selected investment option.

In all scenarios, the link between CNSW and SNW is no longer being reinforced. This suggests that combining storage and controllable DER effectively reduces the need for intrastate reinforcements. This is particularly relevant for NSW, which is expected to have the largest deployment of controllable DER, highlighting the significant role these assets can play in expanding the system. In either case, VIC and TAS still need to strengthen their interconnections through the VIC-SNSW Options and the TAS-VIC interconnections, respectively.