Powering Uncertain Futures

Robust Long-Term Power Grid Planning under Deep Climate Uncertainty: An Exploratory Study for Indonesia

Master thesis

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TU Delft

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Master thesis research by

Timothy de Weijer

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The simulation models, analysis code and DelftBlue scripts developed for this thesis are available on GitLab: https://gitlab.tudelft.nl/hariadiaji/indonesia-power-climate-uncertainties-model.git

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Cover: Image of Indonesia created with ChatGPT
Style: TU Delft Report Style, with modifications by Timothy de Weijer

TU Delft

AI statement

For this work, I used several AI tools for multiple purposes. In short, I used:

- The LLM ChatGPT and its Codex agent for debugging code, helping me write code and building energy simulation models.
- The Overleaf AI assistant and the TeXGPT functionalities to improve my writing and check grammar, spelling, and sentence structure.

For example, I used the ChatGPT AI agent, called Codex, to debug the different models of the Calliope energy system models. I did so by uploading the model files and asking Codex to review the structure and code that I had written. Example prompts include: ”Can you go through the model files and see if there are any indentation errors that might break the model?” and ”Please go over the custom maths constraints and look for any constraints that could make the model infeasible or result in errors.”. I also used ChatGPT to help debug DelftBlue `sbatch` scripts and EMA Workbench scripts by providing the script and the error message and asking questions such as: ”The job fails and gives the error below. What is causing this error and how should the script be modified?” and ”I get an OOM error. What does this error mean and how can I solve it?”. In addition, I used ChatGPT to help with programming tasks when I did not know how to implement a specific function or constraint. Example prompts included: ”Look at my EMA Workbench script below. Can you add a function that scales the values of the CSV with the annual demand I uploaded earlier with 5%?” and ”Can you help me write custom maths constraints for the cc_gas technology? For cc_gas, the capacity in Java-Bali must be equal to 100, in Kalimantan 300, and in Sumatra 300”. I also used ChatGPT to create the cover image. I started with a description of the desired theme and style and iterated with follow-up prompts. Finally, it was used for basic Linux command-line questions, for example: ”How do I move the resulting CSV files from the scratch server on DelftBlue to my own computer and how can I automate this?” or ”How can I automate the step of uploading the resulting CSV to this folder on my own laptop when it is done running?”.

I used the Overleaf AI assistant to help me, for example, in creating the list of abbreviations, tables, and figures. I used the AI tool to organise the tables, for example with the prompt ”Go through the report and make sure that the title of every table is at the top of the table.”. I used the language suggestions given by the AI assistant and the rewrite and synonym functions to improve my wording and sentence structure. Finally, I used the suggested targeted fixes provided by the Overleaf AI assistant when the document was not compiling due to errors.

After using these tools and services, I reviewed and edited the content as needed and assume full responsibility for the content of this work.

Preface

When I started this project, my main supervisor, Igor Nikolic, used a metaphor to write a thesis that has stayed with me ever since. A good thesis, he said, is a bit like an old-fashioned bathtub, with high edges on both sides. You start on one side with a problem. Then you fall into the bath, slowly figuring out what the problem really is until you reach the bottom of both. There, you do many geeky and clever things to investigate the problem and gather results. Finally, you emerge on the other side, presenting and discussing your findings and completing your bathtub. That is where I am now in this thesis, and it is what you, as a reader, are hopefully about to experience. However, before diving head-first, some reflection is in order and some people should be thanked.

This thesis marks the end of almost seven years of studying at the Faculty of Technology, Policy and Management here in Delft. I could never have guessed how much I would learn, both inside and outside the lecture halls. I am extremely grateful for all the experiences I have had here and would choose Delft and TPM again without hesitation. I feel very lucky that these years have led me to something I am now deeply passionate about. Working on the energy transition. Humanity is currently heading towards a climate disaster. If we want to preserve the world as we know it, we will have to move fast, and the only real solution is to move away from a fossil-based system towards one based on renewable energy. At the same time, humanity created this mess, and I strongly believe that we will also find our way out of it. We will do so because we have to and because it is our duty to leave this world a little better than we found it. I cannot wait to contribute to the solution.

I also want to thank the people who made this thesis possible. First, I want to thank my incredible supervisors, who motivated and supported me throughout the entire project. I want to thank Hariadi Aji for his calmness, his extensive knowledge, and his willingness to sit with me every week to solve yet another problem I had encountered. I wish you the very best for the rest of your PhD and cannot wait to see the final results. I would also like to thank Stefan Pfenninger-Lee for his advice on how to tell the story I wanted to tell and for introducing me to the Calliope tool in his CoSEM course, which I found one of the most inspiring courses in the programme. Finally, I want to thank my main supervisor and chair, Igor Nikolic. Instead of a bath, this thesis felt at times more like jumping into a swimming pool with a blindfold on. Without your excellent guidance and help, I would surely have drowned. This work could easily have become my Waterloo, but you helped me turn it into something I am proud of.

A special thanks goes out to all my friends, especially those from De Hoogte and Roltrap, who had to bear with me on the days when everything did not go according to plan. I am surrounded by amazing people and I am grateful to you all.

Perhaps my greatest gratitude goes to my family. To my little brother, thank you for keeping me grounded and reminding me not to act too tough. Mostly, I want to thank my wonderful parents, Arno and Wendy. You taught me to be curious, persistent, and hard-working. Your love and support allowed me to become the person I am today. This work is as much yours as mine.

Y por último, y no menos importante, quisiera darle las gracias a mi novia Celia por su paciencia, amor y apoyo incondicional. De todas las cosas que me han pasado estos dos últimos años, lo mejor ha sido conocerte. Y no te preocupes, pronto te acostumbrarás a mis rarezas holandesas. Quizás no a cenar tan temprano, pero eso lo superaremos juntos..

Hope you enjoy the read!

Timothy A-Jen de Weijer

Abstract

Long-term planning of power infrastructure is central to the energy transition, as new transmission capacity is needed to connect renewable-rich regions with centres of electricity demand. In Indonesia, this challenge is especially relevant because the national long-term electricity plan proposes a supergrid to connect the country's main islands and support decarbonisation until 2060. However, current planning mainly follows a single-path optimisation approach and does not explicitly account for the deeply uncertain effects of climate change. This is problematic because rising temperatures can simultaneously increase electricity demand and reduce the available generation capacity by derating.

This thesis investigates how deeply uncertain impacts of climate change affect Indonesia's long-term power infrastructure plans. It approaches the problem from a Decision Making under Deep Uncertainty perspective, specifically using Robust Decision Making. Rather than assessing whether the planned system performs well in an expected future, the study evaluates whether it remains adequate in many plausible futures, each representing unique combinations of these highly uncertain climate change impacts.

To do so, Calliope energy system models were developed for the Indonesian power system in 2034, 2045, and 2060, using data from Indonesia's state-owned electric utility company PT PLN, the 10-year Electricity Business Plan, the 2060 Long-Term Electricity Plan, and earlier modelling work on power system planning and the energy transition in Indonesia. These models were then used to stress-test different supergrid configurations under uncertain demand increases and capacity derating. Performance was assessed using lost-load hours, levelised system costs, emissions, and regional reserve margins.

The results show that the planned infrastructure performs well from an optimisation perspective, with no lost-load hours in the baseline modelled periods. However, the exploratory analysis reveals that this conclusion becomes fragile under climate stress. Robustness is high in 2034, starts to depend on specific interconnection choices by 2045, and becomes strongly affected by demand increase and derating by 2060. The supergrid therefore acts both as a solution and as a source of vulnerability. Not only does it enable renewable integration, but it also makes system adequacy dependent on a limited number of critical transmission corridors. Reinforcing the Bali–Jawa Timur connection substantially improves robustness, showing that targeted reinforcements can be more valuable than simply maximising all supergrid capacities.

These findings suggest that Indonesia's long-term power infrastructure plan can remain adequate in many plausible climate futures, but only if critical transmission corridors are identified, reinforced and built in time. The study demonstrates that stress-testing long-term infrastructure plans under deep uncertainty can reveal critical vulnerabilities that single-path optimisation approaches may overlook.

List of Abbreviations

Abbreviation	Definition
AC	Alternating Current
ADB	Asian Development Bank
ARED	Accelerated Renewable Energy Development (Scenario)
CC	Climate Change
CCGT	Combined Cycle Gas Turbine
CoSEM	Complex Systems Engineering and Management
CSV	Comma-Separated Values
DC	Direct Current
DMDU	Decision-Making under Deep Uncertainty
EM	Exploratory Modelling
EMA	Exploratory Modelling and Analysis (EMA Workbench)
ERA5	ECMWF Reanalysis v5
GW	Gigawatt
HPC	High-Performance Computing
HVDC	High-Voltage Direct Current
IEA	International Energy Agency
LOLE	Loss of Load Expectation
LTP	Long-Term Planning
MEMR	Ministry of Energy and Mineral Resources (Indonesia)
MWh	Megawatt-hour
MW	Megawatt
OLS	Ordinary Least Squares
PLN	Perusahaan Listrik Negara (Indonesia's State-Owned Electricity Utility)
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCP	Representative Concentration Pathway
RDM	Robust Decision Making
RUKN	Rencana Umum Ketenagalistrikan Nasional (2060 Long-Term Electricity Plan, Indonesia)
RUPTL	Rencana Usaha Penyediaan Tenaga Listrik (10-Year Electricity Business Plan, Indonesia)
SAIDI	System Average Interruption Duration Index
TWh	Terawatt-hour
XLRM	Exogenous Uncertainties, Policy Levers, Relationships, and Measures

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1 Introduction

In this chapter, the research will be introduced by establishing the context, problem statement, and objectives. Section 1.1 provides the necessary background information and the societal relevance of long-term power grid planning in Indonesia. Section 1.2 defines the problem statement, identifying the gap between current planning practice and the need for an uncertainty-aware approach. Section 1.3 states the research objective and its fit within the CoSEM master programme. Section 1.4 outlines the remainder of the report.

1.1. Background and Societal Relevance

Electricity systems around the world are changing rapidly as countries move towards renewable energy to mitigate climate change. In 2022, more than 88% of the newly installed global power came from variable renewable sources, mainly solar and wind (Ghadim et al., 2025). At the same time, global electricity demand is projected to double by 2050 (International Energy Agency, 2021). Together, these trends of increasing variability and growing demand are putting more pressure on power grids. The rise in peak demand requires additional transmission capacity, and greater variability drives a growing need for energy storage to balance fluctuations in supply. This storage requirement, in turn, further increases the demand for transmission capacity during periods of oversupply of renewable energy.

Climate change adds to the challenge. The power sector is highly vulnerable to its effects. Events related to climate change and extreme weather affect all components of the power grid. Increasing temperatures, more intense and frequent storms and increasing sea level, for example, affect the ability of the power grid to generate and transmit electricity (Dumas et al., 2019). Power infrastructures and the electricity they transport are essential for vital societal functions. They play a crucial role in ensuring the safety, health, security, economic and social well-being of people (Gonçalves et al., 2024). Ensuring that they are ready for the developments caused by the energy transition and future climate scenarios is therefore of key societal interest.

To face these new challenges of increasing supply variability, demand, and vulnerability to climate change, existing infrastructure must be further developed. The old infrastructure must be expanded, as it will be exposed more frequently to more extreme climate conditions than the ones for which it was designed, and new infrastructure must be built on top of that (Dumas et al., 2019). These expansions or further developments will come with high capital costs and long lead times (Karlsson et al., 2025). The lifetime of assets is long, and new investments create path dependencies, as they can both hinder and facilitate changes for consumers or electricity providers. As a result, long-term planning (LTP), which takes these factors into account, is crucial for these infrastructures.

Recent PhD research by Hariadi Aji (TU Delft, Faculty of Technology, Policy, and Management) highlights that in Indonesia there is a limited understanding of how climate change uncertainties affect current long-term infrastructure planning (Aji et al., 2025). This matters because Indonesia is particularly exposed to climate risks such as extreme heat, rising sea-level, and flooding (The World Bank Group and Asian Development Bank., 2021). The research by Aji et al. (2026), currently available as a preprint, assessed the vulnerability of Indonesia's power system to climate-related stressors and shocks. They discovered that current and future power plants may be exposed to climate-driven pressures that lower their effective capacity, while rising temperatures simultaneously push up electricity demand. At the same time, heat can derate the generation and transmission capacity, lowering the reserve margins (Aji et al., 2026). Therefore, the impacts of climate change can be expected to have a significant influence on the LTP and the operation of the power infrastructure.

Power system planning in Indonesia is a long process and usually follows a single "best-option" route (Aji et al., 2025). To address climate change, the Indonesian government and the state-owned electric utility PLN have released long-term strategies in the 10-year Electricity Business Plan (RUPTL) and the 2060 Long-Term Electricity Plan (RUKN), establishing a decarbonisation roadmap and the resulting development of the power infrastructure through 2060 (MEMR, 2025a; PT PLN, 2025a). The 2060 Long-Term Electricity Plan also shows the concept of a 'supergrid' which aims to connect the major islands of the nation through High Voltage Direct Current (HVDC) interconnections. The document presents nine major connections specific to this supergrid plan, all of which still have major capacity ranges. These have yet to be determined. The 2060 Long-Term Electricity Plan explains that this long-term infrastructure plan is intended to serve as the backbone to enable greater renewable penetration and to reliably meet future electricity demand. It aims to achieve this by moving power between islands, particularly to address the imbalance between demand, which is concentrated in Jawa–Bali, and the potential for renewable resources, which is located predominantly outside of Jawa-Bali (MEMR, 2025a).

Both the 10-year Electricity Business Plan and the 2060 Long-Term Electricity Plan optimise primarily for costs and carbon emissions. The 10-year plan considers at least a base scenario and an accelerated renewable development (ARED) scenario. The 2060 plan shows a more hydrogen intensive scenario. Neither document clearly accounts for climate uncertainties or for how impacts of climate change could affect the performance of the planned power grid over time.

In addition, climate change is not just another source of uncertainty. It is frequently cited as a source of deep uncertainty (Marchau et al., 2019). Deep uncertainty occurs when the parties to a decision do not know or agree on the likelihood of alternative futures or how actions are related to consequences (Lempert et al., 2003). Put differently, decision-makers do not just lack reliable predictions of the future, but also clarity about which factors will matter at all. For climate change in Indonesia, not only are the projected levels of these risks associated with large uncertainties, but it cannot be said how important they are or will be, since they were not considered when the 2060 Long-Term Electricity Plan and the 10-year energy business plan were developed (The World Bank Group and Asian Development Bank., 2021).

In his work, Aji states that due to this deep climate uncertainty, any basic long-term infrastructure plan will fail (Aji et al., 2025). The Indonesian plan should take into account climate uncertainties by being robust. In practice, this means that it must remain effective across a broad spectrum of possible scenarios. This is how robustness is defined in the field of Robust Decision Making (RDM). RDM is a set of concepts, processes, and tools that use computation, which results in better decisions, not better predictions, under conditions of deep uncertainty (Lempert, 2019). Within RDM, you accept that the future is fundamentally uncertain, and therefore do not attempt to optimise for any single expected outcome. Instead, RDM focuses on developing a robust strategy, which is one that performs satisfactorily in a wide range of plausible future scenarios (Lempert et al., 2003).

RDM is one of multiple approaches in the field of Decision-Making under Deep Uncertainty, or DMDU. DMDU essentially provides a set of methods to guide the decision making process in complex systems. These often contain deep uncertainties and a range of possible policy measures that can be used (Marchau et al., 2019). DMDU approaches typically stress-test the current situation and alternative strategies against a range of possible futures (Marchau et al., 2019). RDM does this through exploratory modelling (EM). EM is used to explore a wide variety of scenarios, alternative model structures, and alternative value systems based on computational experiments (Bankes, 1993). This makes RDM combined with EM a suitable approach for better decision-making in complex systems under deep uncertainties.

In Indonesian power system planning, it is useful to distinguish between (i) current practice, which largely uses single-path optimisation focused on cost and emissions, and (ii) an uncertainty-aware approach, which explores multiple plausible futures and policy options. Here, robustness refers to plans whose performance remains acceptable across many future climate scenarios, assessed in terms of system adequacy (e.g., hours when demand cannot be met), and exploratory modelling is used to stress-test existing plans and policy combinations against deeply uncertain climate impacts.

This thesis is part of the aforementioned PhD research of Hariadi Aji at TU Delft on integrating climate change and adaptive planning into Indonesia's power sector planning, with the goal of developing robust adaptive pathways for a net-zero-resilient power system by 2060 (including inter-island transmission, storage, and infrastructure reinforcement). Within this, the thesis specifically assesses Indonesia's planned supergrid under deep climate uncertainty, examining how uncertainty in demand growth and capacity derating affect system adequacy. It does not develop a full adaptive pathway plan but provides exploratory modelling to show where the current long-term infrastructure plan is robust, where it is vulnerable, and which inter-island corridors are most critical for planning under deep climate uncertainty.

1.2. Problem Statement

The impacts of deep climate uncertainties are not taken into account in long-term planning for the power infrastructure in Indonesia. This thesis aims to stress-test the current long-term infrastructure plan under deeply uncertain climate-driven demand increases and capacity derating, defining infrastructure planning as robust if planned expansions remain effective in many possible future climate scenarios. The effectiveness of the power grid is measured by the number of hours in which the expected demand cannot be met.

To test robustness, the current single-path optimisation approach is extended into an Exploratory Modelling (EM) framework. The output of several models of the energy system for multiple years until 2060 serves as input for an EM analysis. This analysis stress-tests the plans stated in the 2060 Long-Term Electricity Plan and 10-year Electricity Business Plan against uncertain climate change effects. The models are then run over a thousand times against a wide range of futures using different combinations of policy sets, allowing the identification of which plans perform well in most scenarios.

1.3. Research Objective and Fit with CoSEM

A typical CoSEM thesis focuses on the design of complex socio-technical systems. This is a system in which technical components interact with societal elements (such as institutions, human behaviour, and governmental policies) to achieve important societal functions. The Indonesian power grid is a clear example of such a system. There are purely technical components, such as generation and transmission capacity, but there are also important economic aspects. For example, the affordability of electricity consumption and the profitability of power generation. Furthermore, institutional factors influence the system, such as the aim of decarbonisation and the net-zero emission policies implemented by the Ministry of Energy and Mineral Resources (MEMR). As a system, its aim is to enable the societal function of providing a reliable, affordable, and sustainable electricity supply to Indonesia.

This study examines the current long-term infrastructure planning from the 10-year Electricity Business Plan and the 2060 Long-Term Electricity Plan for this system. Currently, the planning process in Indonesia does not consider the impacts of the effects of climate change, although they may be significant. There is a clear need for a more uncertainty aware approach. Including the effects of climate change within long-term infrastructure planning is essential to ensure the reliability of future power systems and deviates from the current optimisation only approach. Incorporating this into the current approach represents a design challenge that is characteristic of CoSEM research.

This research will stress test the long-term power infrastructure plan for Indonesia by looking at its performance in a wide range of future climate scenarios, using the means the PLN has already mentioned in its plans, specifically the inter-island connections in the form of a supergrid. It aims to improve the robustness of the planning of the power system against the future effects of climate change. Ultimately, it could support decision-makers in balancing long-term objectives, such as ensuring a reliable and clean energy supply, against short-term objectives, such as costs. This trade-off exemplifies a typical CoSEM challenge.

1.4. Report Outline

The remainder of this thesis is structured as follows. To gain full insight into the latest academic literature surrounding this topic, chapter 2 reviews the academic literature on long-term power system planning under (deep) climate uncertainty. After identifying the research gap, it will conclude by formulating the main research question. Then, chapter 3 describes the study method chosen to answer this research question, including the reasoning behind the research approach, the Calliope energy system modelling setup, and the exploratory modelling framework used for stress testing. Chapter 4 presents the results of this setup and shows the modelling and exploratory analysis for the three investigated years. Chapter 5 examines the scientific and practical implications of this thesis and outlines the assumptions and limitations that constrain the interpretation of the results. It also offers recommendations for future research. Chapter 6 concludes with answers to the main research question and provides recommendations. The appendices provide additional material (e.g., detailed model assumptions, tables showing the different tested infrastructure configurations over the years, and extended model results) that supports the chapters but is not required to follow the main story.

2

Literature Review

This chapter reviews the latest academic literature that is relevant for long-term planning of power systems under deep climate uncertainty. The chapter concludes by identifying the knowledge gap that motivates the research question. Section 2.1 describes the search plan and defines the core concepts used in the search strategy. Section 2.2 analyses the resulting body of literature, identifying the key knowledge gap in three groups of studies. Section 2.3 translates that gap into the main research question that guides this thesis.

2.1. Search Plan and Core Concepts

First, this review examines the recent academic literature on long-term planning of power systems under climate uncertainty. The PRISMA search strategy is used to identify suitable articles. The PRISMA method is a standardised approach for conducting literature reviews. It provides a transparent process for identifying, screening, and selecting studies, ensuring that the review is unbiased (Trifu et al., 2022). This method is particularly useful for identifying gaps in the existing literature (Trifu et al., 2022).

Core concepts were identified and combined into a search string that was queried in the Scopus database. The first core concept is *deep uncertainty*. Originally from the DMDU and RDM literature, it describes situations in which parties to a decision do not know or cannot agree on what the future might look like, how the system works, or what outcomes are most relevant (Lempert et al., 2003). In this study, *climate change* is recognised as a source of deep uncertainty with direct implications for Indonesia's power infrastructure. A further key concept is that such uncertain impacts of climate change are currently not incorporated in long-term infrastructure planning. For example, the supergrid expansion planning in the 2060 Long-Term Electricity Plan follows a single ”best-option” route and does not consider that currently negligible variables, such as temperature-driven derating of generation capacity or increases in load demand, may become significant in the future.

In his paper, Aji et al. (2025) reviewed the literature on long-term decarbonisation planning for Indonesia and concluded that the uncertainties of climate change have not been rigorously discussed and that a more robust approach is necessary. Several of the papers identified in that review are included here. However, the scope is broadened to examine the wider literature on the use of RDM and DMDU to account for climate uncertainties in long-term planning of power infrastructure, including contexts beyond Indonesia.

The initial search combined terms related to deep uncertainty, climate change, and long-term planning of power infrastructure, but this yielded insufficient results. The search was therefore split into two sub-searches: one focusing on infrastructure expansion planning and deep uncertainty, and one focusing on long-term power infrastructure planning and climate change impacts. Both searches and the included synonyms are shown in Figure 2.1. The search was restricted to peer-reviewed articles published between 2015 and 2025 and resulted in 104 articles. After removing duplicates, 102 remained. The titles, abstracts, and keywords were then screened, excluding papers focusing on DC grids, micro-grids, or smart-grids, which are all outside the scope of this research. Papers that did not address long-term planning for the power infrastructure in relation to either the effects of climate change or mention deep uncertainty were also excluded. This screening step left 26 articles for eligibility assessment.

To assess eligibility, the introduction, results, and conclusion sections were read. Papers focusing on resilience rather than robustness were excluded, as they emphasise rapid restoration after failures instead of planning that remains adequate in many plausible future scenarios. In addition, papers that only constructed a linear optimisation energy model for decarbonisation with cost minimisation as the sole objective were excluded. This process left 9 articles. Together with two additional articles identified via Aji et al. (2025), the final set comprised 11 articles for review (Figure 2.1). These can also be found in the appendix A.2.

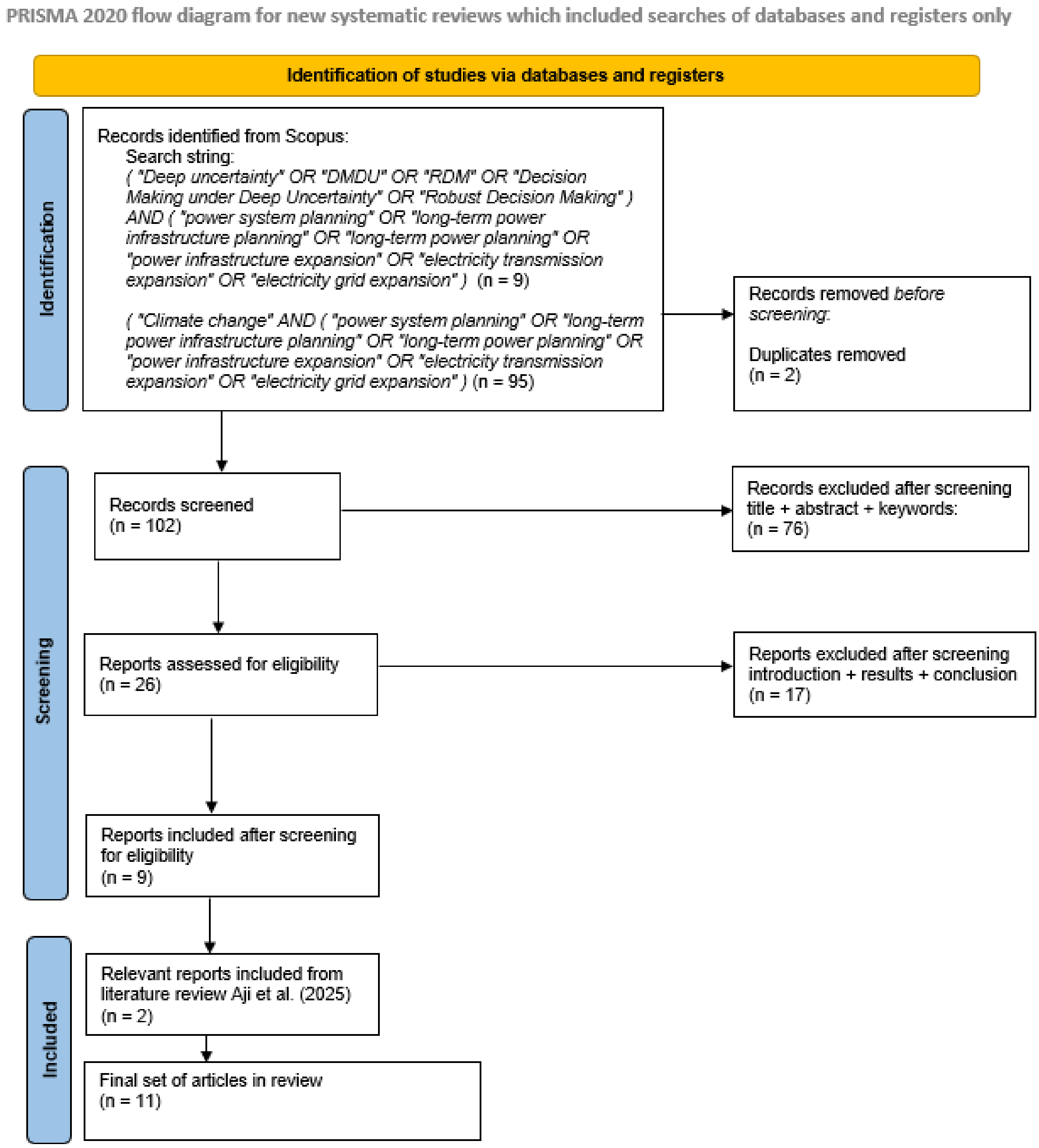

Figure 2.1: PRISMA table.

2.2. Knowledge Gap

The literature relevant to this study falls into three broad groups. These are studies on Indonesia's decarbonisation planning, studies that model the effects of climate change on power systems, and studies that apply DMDU methods to power infrastructure planning. Looking closely at what these papers offer and what they overlook exposes a distinct gap that remains unaddressed.

In their paper, Aji et al. (2025) already concluded that deep climate uncertainties are not included in long-term power infrastructure plans for Indonesia. They found that research on climate uncertainties and their impact on Indonesia's decarbonisation plans has been very limited, with existing work focusing mainly on cost-optimal pathways using optimisation methods. The studies he reviewed confirm this pattern. Langer et al. (2024) model the future Indonesian power system to net-zero by 2050 and identify interconnection and energy storage as crucial tools, but base installed capacities on technological potential rather than existing policy plans, and do not include climate change as an uncertainty. Handayani et al. (2022) go one step further by explicitly identifying climate change as a risk to the power system, but do not model its actual impact. These Indonesian-specific studies share a common weakness. They all optimise for a single trajectory and treat the future as knowable, which is precisely what the DMDU literature argues is inappropriate when facing deep uncertainties such as those posed by climate change (Lempert et al., 2003; Marchau et al., 2019).

Zooming out, several papers discuss taking the effects of climate change into account for power systems planning. Wang et al. (2025) show that climate change alone could increase total energy system costs by an estimated 20% by 2050, driven by the compounding effects of increased demand, declining thermal efficiency, and variability of renewable output. Craig et al. (2020) demonstrate how thermal derating during high-stress periods can directly endanger the security of supply. Sherman et al. (2022) find that increases in demand due to rising temperatures already exceed what current grid infrastructure can handle and must be considered in future planning. Rosende et al. (2019) show that including climate effects leads to earlier and more extensive transmission expansion. Haddad et al. (2025) show that the expansion of the infrastructure can compensate for climate-driven reductions in the output of hydropower, demonstrating that the expansion of the infrastructure can function as a tool to alleviate the effects of climate change. Together, these studies establish that climate change simultaneously increases electricity demand and reduces generation and transmission capacity, creating a compounding pressure that long-term planning cannot safely ignore. However, each study only varies a narrow slice of the uncertainty space. Haddad et al. (2025) vary only hydroelectric power and consider just two policy scenarios, while Wang et al. (2025) perform a single-route optimisation focused on costs, and Rosende et al. (2019) model one deterministic climate trajectory. None treats climate change as the deep uncertainty that it is recognised to be.

Bloomfield et al. (2021) make this limitation explicit. Looking at European power systems, they show that climate models are sufficiently inconsistent with one another that preparing for a wide range of possible futures is more appropriate than optimising for any single projection. They concluded that incorporating climate uncertainty more thoroughly into power system design is an important and unresolved research avenue. Santos et al. (2016) explain that power system planning leads to a problem of "deep uncertainty." They argue that robust methods are needed to identify and investigate alternative strategies and long-term plans across a range of possible future scenarios, taking into account deep uncertainties such as those associated with climate change. This approach also helps you uncover where these strategies are vulnerable, understand the trade-offs between them, and examine which policies remain effective under different uncertainties, thereby increasing their robustness.

Some studies operationalise these robust methods. Paredes-Vergara et al. (2025) identify RDM as the most suitable DMDU method for power systems planning and apply it to the Chilean system in 1000 simulated cases, quantify the trade-off between emissions and costs, and compare the resulting robust strategy with conventional plans. Sundar et al. (2024) similarly develop a decarbonisation pathway that remains robust across hundreds of possible climate realisations, showing that modest additional investment can substantially improve robustness on the path to net-zero. These studies demonstrate that RDM is both feasible and valuable for planning power infrastructure under deep uncertainty. However, each contains a critical blind spot. Paredes-Vergara et al. (2025) apply RDM but do not include climate change itself as one of the uncertainties being stress-tested. Sundar et al. (2024) do incorporate climate-driven inputs, but find no investment in inter-regional transmission in any of their robust pathways. They attribute this result to their climate-driven input data being daily, and with daily resolution you often cannot capture hourly peaks in wind or solar output and net load, which often create the economic value for more transmission capacity. Their conclusions therefore focus on generation adequacy rather than grid infrastructure.

Together, these findings are summarised in Table 2.1. A clear pattern emerges. Climate impact studies confirm that rising temperatures simultaneously drive up demand and derate generation and transmission capacity, yet they treat climate as a deterministic or narrowly bounded input rather than a deep uncertainty. DMDU studies provide appropriate methods for handling this uncertainty, but either exclude climate change from the uncertainty space or focus on generation rather than infrastructure. Indonesia-specific studies qualitatively acknowledge climate risk but do not incorporate it into their planning models (Aji et al., 2025; Handayani et al., 2022; Langer et al., 2024). As a result, the reviewed literature does not contain an application of a DMDU approach to stress-test long-term power infrastructure plans against deeply uncertain climate change impacts. In addition, none focused on Indonesia, a country that is highly vulnerable to climate risks and is pursuing an ambitious grid expansion through the supergrid concept in the 2060 Long-Term Electricity Plan. Therefore, the remaining gap is not whether climate change matters for power systems or whether DMDU methods are useful, but how Indonesia's long-term transmission expansion planned performs when climate impacts are treated as deeply uncertain. This thesis addresses that gap by stress-testing the planned infrastructure pathways for 2034, 2045, and 2060.

Table 2.1: Overview of literature included in the literature review.

Article	Indonesia-specific	Climate impact modelled	Single-route optimisation	Climate uncertainty	DMDU method applied	Infrastructure focus
Aji et al. (2025)	✓		✓			
Langer et al. (2024)	✓		✓			✓
Handayani et al. (2022)	✓		✓			
Haddad et al. (2025)		✓	✓			
Wang et al. (2025)		✓	✓			
Craig et al. (2020)		✓	✓			
Sherman et al. (2022)		✓	✓			
Rosende et al. (2019)		✓	✓			✓
Bloomfield et al. (2021)		✓		✓		
Santos et al. (2016)				✓	✓	
Paredes-Vergara et al. (2025)				✓	✓	✓
Sundar et al. (2024)		✓		✓	✓	

2.3. Main Research Question

Climate change can have a significant impact on Indonesia's long-term power system plans, yet existing studies only qualitatively acknowledge this and do not incorporate it into decarbonisation pathways. Climate change uncertainties are recognised as deep uncertainties in the literature, for which Decision Making under deep uncertainty (DMDU) approaches such as Robust Decision Making (RDM) are required. However, studies applying these methods either do not treat climate change as an explicit uncertainty or focus primarily on the adequacy of the generation capacity rather than planning the power infrastructure. As a result, there is a lack of research assessing the robustness of Indonesia's long-term power infrastructure plans under deeply uncertain climate change impacts. Based on this knowledge gap, identified in the previous section, the main research question of this thesis is the following.

What is the impact of deeply uncertain effects of climate change on Indonesia's long-term power infrastructure plans?

In the next chapter, the research methods used to address this question and its resulting sub-questions will be presented and justified.

3

Study Design

This chapter describes the research design used to investigate the impact of deeply uncertain climate change on Indonesia's long-term power infrastructure plans. Section 3.1 justifies and explains the research approach, including the sub-questions and methods in subsection 3.1.1, the data requirements and sources in subsection 3.1.2, and the research flow diagram in subsection 3.1.3. Section 3.2 describes the Calliope energy system modelling setup, covering demand (3.2.2), generation and storage (3.2.3), and transmission (3.2.4). Section 3.2.4 details the exploratory modelling setup using the XLRM framework and EMA Workbench.

3.1. Research approach

The gap addressed in this study is that the long-term power infrastructure plan for Indonesia does not account for the deeply uncertain effects of climate change. These effects are not only uncertain but deeply uncertain, which means that decision-makers cannot agree on the probability of alternative futures or on how important these effects will be (Lempert et al., 2003). As established in Chapter 1, Indonesia is highly vulnerable to the effects of climate change, such as increasing temperatures. The current single-path optimisation approach used in the 10-year Electricity plan and the 2060 Long-Term Electricity Plan treats the future as knowable. Demand, for example, is treated as a fixed figure per island. This is precisely what the literature argues is inappropriate under sources of deep uncertainty such as climate change (Lempert et al., 2003; Marchau et al., 2019).

The core challenge is that the Indonesian power system is a complex socio-technical system in which the consequences of infrastructure decisions made now play out over decades. These decisions involve high capital costs, long lead times, and are highly sensitive to future conditions that cannot be predicted with confidence. Climate change adds complexity. As shown in the review of the literature, it can simultaneously increase electricity demand and reduce generation and transmission capacity, creating compounding pressures (Craig et al., 2020; Sherman et al., 2022; Wang et al., 2025).

This creates three key requirements for the research approach. First, the approach must be able to simulate the performance of power infrastructure across a wide range of plausible futures, rather than optimising for a single expected outcome. Second, it must be able to systematically explore the interaction between infrastructure choices and climate uncertainty, identifying which plans remain adequate in many scenarios and where they break down. Third, it must remain computationally feasible given the scale of the Indonesian system, while still capturing the critical stress periods that determine whether infrastructure plans succeed or fail.

These requirements point toward a modelling approach and more specifically toward an exploratory modelling (EM) approach within the Robust Decision Making (RDM) framework. Model-based energy scenario studies are widely used to guide decisions in complex energy systems, because they allow the performance of infrastructure to be evaluated in different scenarios without the need to physically build costly infrastructure (Cao et al., 2016). The inherent complexity of the Indonesian system, with its many direct and indirect interactions between generation, transmission, demand, and climate, means that the consequences of interventions cannot be easily predicted analytically and therefore simulation is necessary.

However, standard optimisation modelling alone is insufficient here. As demonstrated in the review of the literature, the existing studies for Indonesia rely on single-route optimisation and treat the future as knowable, which does not address the deep uncertainty that characterises climate change (Aji et al., 2025). A model that produces an optimal solution cannot reveal how robust that solution is or where it becomes vulnerable. What is needed instead is an approach that stress-tests plans across many possible futures.

Exploratory Modelling is designed precisely for this purpose. By running a simulation model many times under systematically varied combinations of uncertainties and policy choices, EM enables systematic exploration of the solution space (Bankes, 1993). For this thesis, this involves identifying which possible infrastructure combinations, derived from the connections proposed in the 'supergrid' plan, perform well in a wide range of plausible future scenarios and which do not, as well as determining the specific conditions under which they fail. Using the RDM framework, this replaces the goal of finding the optimal plan with the goal of finding a robust one, which means that it performs satisfactorily across a wide range of scenarios, even if it is not optimal for any single projection (Lempert et al., 2003). At the same time, a modelling approach has limitations that should be kept in mind. Two important ones are availability bias and the 'garbage in, garbage out' principle.

Availability bias refers to modellers including their own knowledge of historic events in their reasoning behind model parametrisation or methodology. They might have forgotten to account for unexpected or disruptive elements (Gregory & Duran, 2001). For this research, this could appear in the way uncertainties, policy measures, or data ranges are selected. The assumptions may under-represent unexpected disruptions, such as extreme weather events or technological breakthroughs. For example, battery costs may decline faster than expected. Similarly, intervention selection can be based on current policy documents. Other future options (like nuclear modular reactors) might emerge but remain excluded due to current bias. The principle of 'garbage in, garbage out' refers to the fact that the model results depend on the accuracy of the input data and assumptions (Aughenbaugh & Paredis, 2004). For example, future demand growth or transmission expenses might be underestimated. In that case, the outcome of the EM analysis could indicate that infrastructure planning appears sufficient on paper, yet in reality it would either be prohibitively costly or fail to provide enough capacity.

3.1.1. Sub-Questions and Research Methods

To organise and structure the research, the primary research question is divided into two sub-question. The main research question to be addressed is:

What is the impact of deeply uncertain climate change impacts on the long-term power infrastructure plans of Indonesia?

The first sub-question looks at the current planning through metrics relevant for PT PLN, who are responsible for the supergrid plan. Different versions of infrastructure planning for Indonesia were modelled using the most up-to-date data from the 10-year Electricity Business Plan and 2060 Long-Term Electricity Plan on future demand, generation capacity, and (inter-regional) transmission capacity for several years until 2060. The Calliope energy system modelling framework was used for this purpose.

For the second sub-question, climate change effects are incorporated. The XLRM framework was used to perform an exploratory analysis using EMA Workbench. With the EMA Workbench, several versions of the infrastructure planning were stress-tested against the deeply uncertain climate change effects. For each sub-question, the method used to obtain the answer, along with its limitations, is described in the remainder of this chapter. Together, the answers to these sub-questions address the main research question.

Sub-question 1.

How does the current long-term power infrastructure plan of Indonesia until 2060 perform against the key metrics of the number of hours with lost load, levelised system costs, total emissions and regional reserve margin?

The four metrics examined in this sub-question were chosen because, taken together, they represent the key planning goals of Indonesia's long-term power infrastructure strategy. Lost-load hours indicate system adequacy, levelised system costs represent affordability, total emissions reflect Indonesia's decarbonisation target, and regional reserve margins indicate whether sufficient capacity is available in different parts of the Indonesian power system. These are also the indicators cited in the policy documents drawn upon in this thesis (MEMR, 2025a; PT PLN, 2025a).

To answer the first sub-question, an energy system model of the Indonesian power system was constructed in the Calliope Energy System Optimisation Model. This model was selected for a few reasons. A key reason is that Langer et al. (2024) used this model in their study. They used Calliope because of its high spatial and temporal resolution, its ability to use publicly available cost data in an objective and transparent way, and because it has already been used to model a variety of energy systems across geographical contexts and scales. The use of a temporal resolution of at least one-hour is seen as necessary to model intermittent supply. High spatial resolution is needed to accurately estimate the costs of interconnection capacities. With Calliope, assumptions and pathways from the 10-year Electricity Business Plan and 2060 Long-Term Electricity Plan plans can be implemented relatively easily. Although Langer et al. (2024) used Calliope version 0.6, this study adopts version 0.7, which offers greater stability and is expected to reduce computational errors (Pfenninger & Pickering, n.d.). An additional advantage of employing the model developed by Langer et al. (2024) is that reusing its structure substantially reduces the time required for the making of the Calliope models. The differences in basic model structure between their work and this research are explained in section 3.2.

For the purposes of this study, it is not necessary to simulate a whole year, as was done by Langer et al. (2024). The robustness of the plan can instead be evaluated based on its performance during the most critical periods of the year. If the plan is effective under these conditions, it can reasonably be assumed that it will function adequately throughout the year. Peak demand is particularly crucial, as the adequacy of the system is more likely to be stressed during evening peak hours, when electricity demand in Indonesia is highest and solar generation is typically at its lowest. Appendix Figure A.5 shows the normalised typical daily demand in 2034 over all nodes on the island of Sumatra. It shows this peak demand around 19:00. The 2060 Long-Term Electricity Plan indicates a very large uptake in solar capacity up to 2060. The selected periods must reflect the most challenging combinations of scarce renewable output and high demand. Consequently, the weeks with peak national demand and peak demand in each sub-system, in this case the major islands of Indonesia, are of greatest interest. If the planned system can satisfy demand under these conditions, even when additional climate-driven derating and demand increases are taken into account, it is unlikely to fail in less extreme weeks. This approach reduces computational time and makes it possible to explore a larger number of scenarios using EM.

As stated above, this study focuses on the main islands of Indonesia. Interconnections are highly capital intensive. The significant costs and distances involved in connecting smaller or widely dispersed islands make full integration economically and technically improbable. In addition, these four island systems contain nearly all the potential and demand of Indonesia's electricity generation. Sumatra and Kalimantan have the renewable potential, while Jawa–Bali concentrates most of the electricity consumption. A limitation of the model is its scale. Since this study concentrated on the entire country of Indonesia, it cannot fully represent reality (Pfenninger et al., 2014).

It is unnecessary to construct a model for every year up to 2060. Instead, a few strategically chosen years can represent the evolution of the system over time. The year 2034 is the last year with detailed planned supply data in the 10-Year Electricity Business Plan. The year 2045, roughly midway between 2034 and 2060, is when all supergrid transmission lines are planned to be fully built, while fossil fuel–based generation capacity remains in the system. By 2060, electricity demand is projected to have increased substantially and dispatchable generation capacity is expected to be minimum, largely replaced by renewables and sustainable alternatives (MEMR, 2025a). Therefore, these three years are selected as key reference points in assessing the robustness of long-term power system planning.

After formulating the model for 2034, 2045, and 2060, it is executed to evaluate system performance against predefined metrics, answering this sub-question. The outcomes also provide the basis for the next sub-question, in which alternative configurations are evaluated under deep uncertainty related to climate change impacts.

Sub-question 2.

What impact do the deeply uncertain effects of climate change have on the robustness of different infrastructure development plans?

The XLRM framework and the Calliope models from the previous sub-question are used to stress test the current plan against deeply uncertain climate change effects. The XLRM framework was developed by Lempert et al. (2003) as a tool for DMDU. The XLRM framework offers a structured way to explore complex systems under deep uncertainty. It helps organise information relevant to decision-making and supports developing the wide range of future scenarios needed later for the EM.

The framework groups the analysis into four categories. Uncertainties (X) are external factors beyond the control of decision-makers. The policy levers (L) are actions that, when combined, form the strategies available to decision-makers. In this research, the key levers are decisions on whether to build supergrid connections and, if so, what capacity these connections should have. Relationships (R) describe the system interactions that shape how the future evolves based on the chosen levers and how uncertainties unfold. Measures (M) are the criteria, such as costs, by which decision-makers assess system performance and evaluate different infrastructure strategies and scenario desirability (Lempert et al., 2003).

To answer this second sub-question, the XLRM framework was filled out based on the 10-year Electricity Business Plan and the 2060 Long-Term Electricity Plan (MEMR, 2025a; PT PLN, 2025a). Then, the analysis examined how deeply uncertain climate change impacts influence model outcomes when applying (combinations of) different infrastructure levers from the plan through 2060. An EM approach was adopted. This requires a simulation model (the Calliope model) and a tool that supports EM. Currently, this combination does not exist for Indonesia. Therefore, the Calliope simulation model was linked with the EMA Workbench, a tool that supports EM (Kwakkel, 2025).

Calliope is well suited to optimise power and transmission capacity, but it cannot systematically explore the performance of key measures under combinations of specified uncertainties and policy levers. The EMA Workbench is designed exactly for this purpose. As a workbench, it systematically explores large ensembles of plausible futures via exploratory modelling (Bankes et al., 2003), supporting the identification of robust rather than optimal decisions (Bankes et al., 2003).

The EMA Workbench can be used to define an uncertainty space and infrastructure lever levels. Instead of focusing on all impacts of climate change, this research focuses on derating from temperature increases and potential demand growth from the same effect. These were identified as key vulnerabilities for Indonesia (Aji et al., 2025). Using EMA Workbench, this study ran between 1000 and 1600 model experiments per investigated year to explore uncertainty in derating and demand increase, and evaluate how robust different lever combinations are to these effects, for 2034, 2045 and 2060.

First, the EMA Workbench directed search functionality was applied to identify promising candidate strategies for stress tests in 2045 and 2060 (Kwakkel, 2023b). Because supergrid lines have very large uncertainty ranges, this approach allowed for the removal of policies that did not perform sufficiently well in any scenario. After selecting these candidate strategies, variations of these strategies, together with the strategies using the minimum and maximum feasible capacities, were examined in a range of scenarios to determine which strategy or strategies are the most robust. The analysis focused on which levers most affect the number of lost load hours and which lever combinations produced robust infrastructure planning up to 2060.

Derating, or the reduction in delivered generation and transmission capacity, is represented in terms of active power (MW). For precise values, this study relies on data from research done by Aji et al. (2026). This data set provides projected capacity losses for various temperature increases by province, resulting from the derating of generation capacity up to the year 2060. It also includes estimates of potential demand increases as a function of rising temperatures.

A limitation of this method is that the results are contingent upon the defined uncertainty bounds. Therefore, it cannot represent the full range of potential climate impacts. Another is that the results depend greatly on the range of the uncertainty set explored. They provide more insight into robustness patterns than definitive predictions or guarantees (Bankes et al., 2003).

3.1.2. Data Requirements and Data Sources

For sub-question 2, the structure of the model of Indonesia of Janis Langer will be used. The Calliope code is open-source and the model contains several important data requirements, such as demand profiles for 2030, 2040, and 2050, generation and storage technologies, and key data on High Voltage Direct Current (HVDC) technologies (Langer et al., 2024). Demand and generation datasets are structured as hourly CSV files, compatible with the time-indexed format of Calliope.

For this study, the existing model must be updated using the most recent policy document issued by the Indonesian government. This document provides projected technology capacities over the next 35 years, estimated demand up to 2060, and the supergrid development plan (MEMR, 2025b). It shows a map with the connections planned so far, their date of commencement, and the potential ranges for the capacity. In addition, the 10-Year Electricity Business Plan of Indonesia's state-owned utility PT PLN offers more detailed and complementary information up to 2034, including additional planned generation capacity and forecast electricity demand by province (PT PLN, 2025a).

In the original model Langer et al. (2024), a single demand profile was applied, based on Malaysia and Kalimantan, to all provinces. For the models used in this thesis, the province-specific demand demand values are used to construct the demand for 2034. This was done using Sumatra and Jawa demand profiles and 2024 demand data provided by Hariadi Aji of PT PLN. The demand profiles for Kalimantan and Sulawesi are based on those of Sumatra. However, the total annual electricity demand in 2034 for each province aligns with the 10-year Electricity Business Plan projections, while the evolution of demand for subsequent years up to 2060 will follow the expected growth from the 2060 Long-Term Electricity Plan.

Finally, data from Aji et al. (2026) were used on increase in demand at the province-level and technology-specific derating under rising temperatures driven by climate change. The derating assumptions are presented in Table A.5, and the demand increase assumptions are shown in Table A.6. Thermal generation units experience capacity losses as ambient temperatures rise, affecting either air inlet conditions or cooling water temperatures. For photovoltaic, the study applied a simplified derating function based on irradiance and temperature. For changes in temperature-driven demand, the study estimates the sensitivity of electricity demand to temperature using an ordinary least squares regression model, relating the daily maximum ambient temperature of ERA5 to daily province-level electricity demand data from PLN.

3.1.3. Research Flow Diagram

Figure 3.1 shows the research flow diagram for this research. It shows the in- and output per chapter, the tools and methods used per research phase, and the division between the sub-questions.

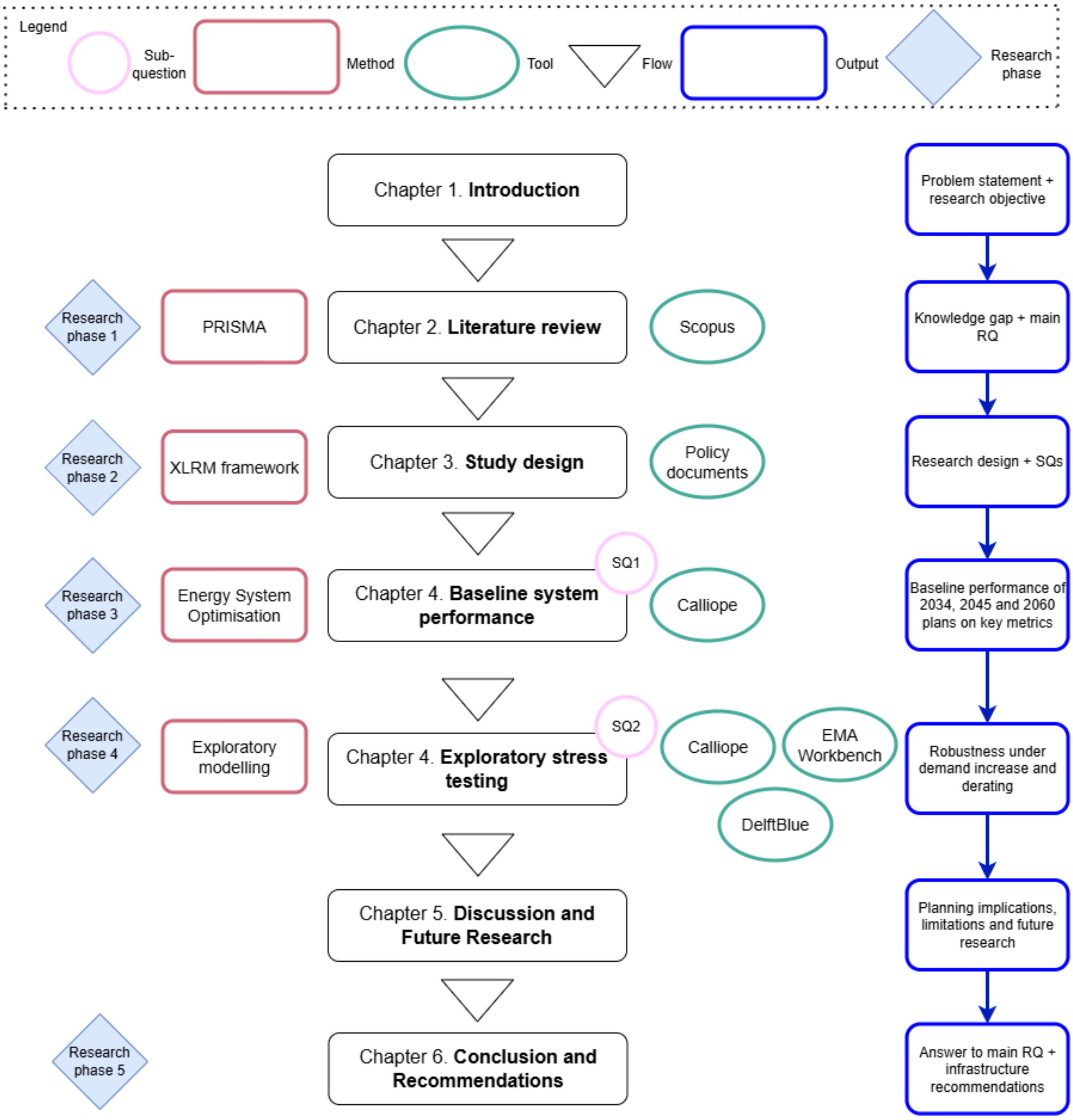

Figure 3.1: Research flow diagram

3.2. Energy system modelling setup

This chapter presents an overview of the Calliope set-up used for the years 2034, 2045, and 2060. It starts by highlighting how the Calliope models in this work differ and are similar to the model developed by Langer et al. (2024). Calliope represents regions as nodes and links them through interconnections to describe how they produce, consume, store, and exchange energy carriers (Pfenninger & Pickering, 2018). For this study, the analysis focuses only on electricity and avoids other energy carriers such as heat and hydrogen, which keeps the complexity of the model and the run time computationally feasible but omits sector-coupled solutions for the entire energy system. As mentioned above, the analysis is limited to the main islands of Jawa, Sumatra, Kalimantan, and Sulawesi. The islands of Nusa Tenggara Barat and Nusa Tenggara Timur are each represented as a single node and are included because, in the supergrid plan, they lie along the connection between Jawa and Sulawesi. Bali and Kepulauan Bangka Belitung are also included, as they are already connected to Sumatra and Jawa, respectively, through existing AC transmission lines. This means that there are a total of 29 nodes in the model.

A location and technology-independent discount rate of 10% is assumed, as used by Langer et al. (2024). Calliope identifies the necessary generation, storage, and transmission capacities needed to satisfy demand while remaining within the user-defined boundaries. The optimisation process in Calliope aims to minimise overall system costs. The methods and materials for demand, generation, storage, and transmission are described below.

3.2.1. Updates to the Existing Indonesian Calliope Model

The Calliope models developed in this study are based on the Indonesian power system model of Langer et al. (2024). Several core modelling choices are retained. Renewable generation profiles for solar, wind and hydropower are reused, as are the general representations of AC and HVDC transmission technologies and their technical specifications. The model also follows Langer et al. (2024) in not applying ramping constraints and in reusing most of the geographical nodes that make up the model.

At the same time, the model is updated in several important ways to align it with the 10-year Electricity Business Plan and the 2060 Long-Term Electricity Plan policy documents. Technologies that are not included in these plans, such as floating solar, are removed, while technologies with explicit policy goals, such as ammonia, biogas, and hydrogen-based generation, are added (MEMR, 2025a; PT PLN, 2025a). The transmission network is also revised. Not all AC links from the original model are kept, but only those supported by the most recent policy documents. In addition, the model implementation is adjusted so that AC and HVDC links are defined directly in the main model configuration, rather than being loaded from a separate input file. For the 2045 and 2060 models, additional custom mathematical constraints are introduced to enforce technology capacity targets per main Indonesian island from the policy documents. Together, these updates ensure that the model can reflect the most recent planning of the future power infrastructure and can be used to evaluate the supergrid development pathways from 2034 to 2060.

3.2.2. Province-Specific Electricity Demand Modelling

To simulate the Indonesian electricity system, demand data per province are required. As stated above, the provincial demand data for the Sumatra and Jawa islands in 2024 were given by Hariadi Aji of PT PLN. The original data for 2024 used half-hour values. These were converted to hourly values to align with the model of Langer et al. (2024). In the 10-year Electricity Business Plan, there is a predicted annual demand value per province until 2034 in TWh (PT PLN, 2025a). The analysis in this research starts with 2034, as this is the last year for which provincial predictions are available. Using the 2024 power profiles, the hourly demand values were scaled so that the yearly demand per province would match that of the 10-year Electricity Business Plan. To determine the demand for 2045, 2050 and 2060, the predicated yearly demand value for the main islands in the 2060 Long-Term Electricity Plan was used (MEMR, 2025a). For the islands of Kalimantan, Sulawesi, and Nusa Tenggara Barat and Nusa Tenggara Timur, the average profile of Sumatra was used.

The most relevant threat to grid stability is the surge in peak demand beyond the available transport capacity, triggering forced power cuts. This peak demand is strongly influenced by ambient temperature. Higher temperatures can increase electricity demand while simultaneously decreasing available generation capacity through derating (Aji et al., 2025). Together, these effects sharply increase the pressure on infrastructure, as more power must be pulled from elsewhere. By simulating a set of key weeks, the approach enables stress-testing of the infrastructure plans for both high daily peaks and longer term fluctuations. The demand data shows that national and subsystem peaks all hit in the month of October. Therefore, October is used as the reference month for running the model.

3.2.3. Generation Technologies, Storage, and Capacity Assumptions

For this study, a set of generation and storage technologies was used. The economic and technical assumptions of these technologies can be found in the Appendix Tables A.2 and A.3. As mentioned above, the 10-year Electricity Business Plan showed detailed information on the generation capacity available in each province until 2034. This allowed the generation capacities for all the nodes in Calliope to be fixed.

The 10-year Electricity Business Plan runs until 2034. After that, the 2060 Long-Term Electricity Plan is used. The 2060 Long Term Electricity Plan does not provide detailed provincial generation capacity, but does provide capacity targets for subsystems or islands (Jawa, Sumatra, Kalimantan, Sulawesi, Nusa Tenggara, Kepulauan Maluku and Papua). These targets were used to define the constraints of the generation capacity in the Calliope model, ensuring that each island reaches its local goal. The optimisation of Calliope then determined the capacity per island, which was fixed for the subsequent exploratory analysis. Keeping generation capacity fixed ensured that a single iteration of the model converged much more quickly than it would have if the model also had to determine capacities.

3.2.4. Transmission Network Topology and Capacity Assumptions

The basic network topology is shown in Figure 3.2. The network without any of the supergrid infrastructure plans is based on the work of Langer et al. (2024) and the current and planned AC connections retrieved from the 2060 Long-Term Electricity Plan. It is assumed that onshore transmission is implemented with alternating current (AC) lines, whereas links to islands are based on subsea high-voltage direct current (HVDC) cables, except for the line between Jawa and Bali. This line is already in place, is included in the supergrid plan, and will continue to be AC, only with increased capacity. The analysis focuses solely on the active power flows in the lines and therefore disregards aspects such as voltage, frequency, and apparent power. The active power available on a line depends on the type of line, as defined in the 2060 Long-Term Electricity Plan plans. It is assumed that each line has 2 conductors and that its capacity is constrained by dynamic stability, taken as one-third of the rated power. Appendix Table A.12 summarises the maximum capacity for each AC transmission line.

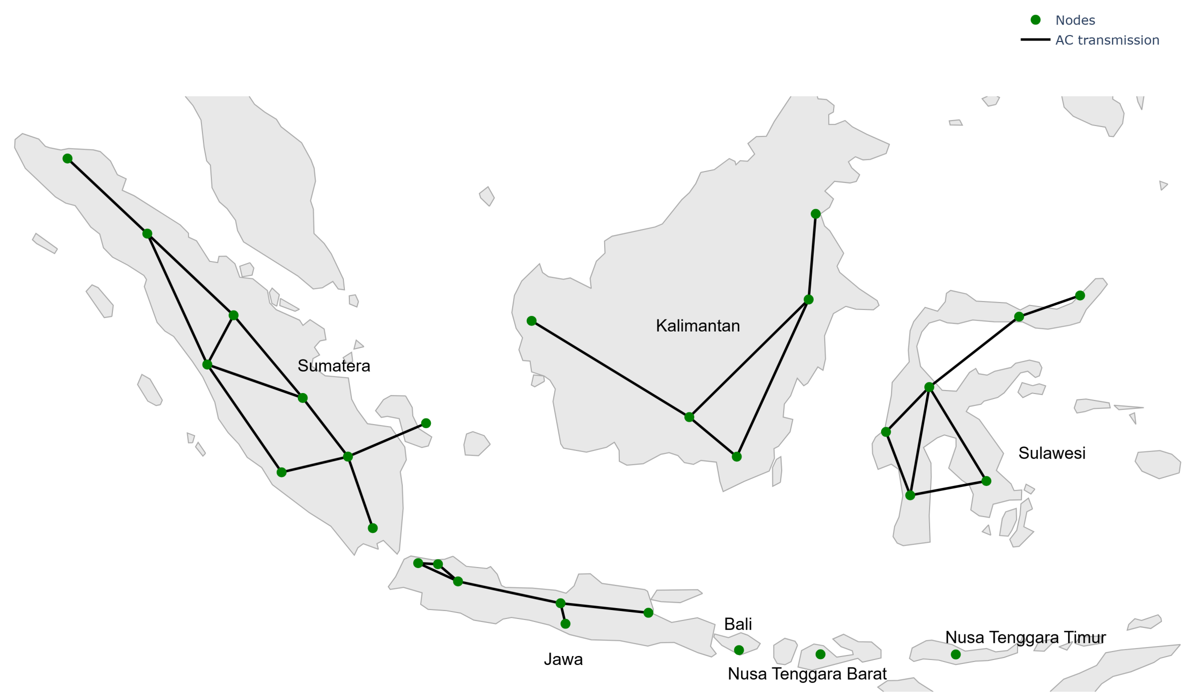

Figure 3.2: Network topology in 2034 without any supergrid lines

3.3. Exploratory modelling setup

To assess the impact of the deeply uncertain effects of climate change, the XLRM framework was used to systematically structure the Indonesian system. The XLRM methodology has been described in detail in Chapter 3.1.1. The results can be seen in Figure 3.3.

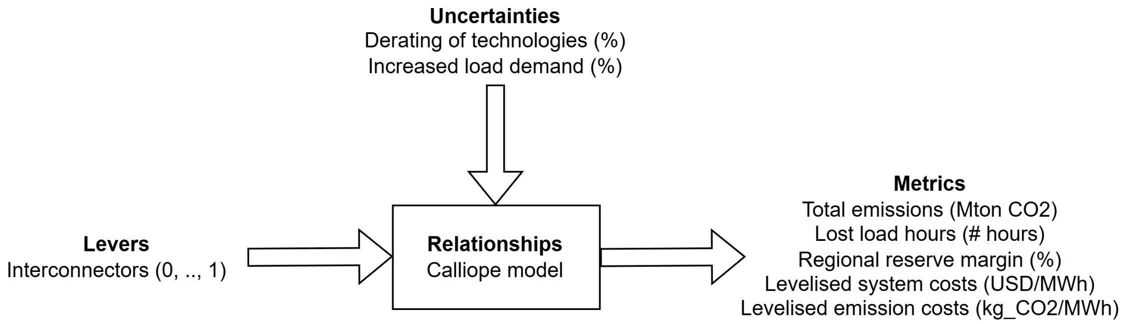

Figure 3.3: XLRM framework

Figure 3.3 shows the different components of the XLRM framework. The policy levers under investigation correspond to the planned high-voltage direct current (HVDC) interconnection lines between the islands of Indonesia. The location and nominal capacities of these lines are derived from the 2060 Long Term Electricity Plan (MEMR, 2025a). Because the 2060 Long-Term electric power plan defines capacity as ranges rather than precise values, multiple levels of interconnection capacity are tested, from no interconnection to the maximum capacity specified in the planning documents.

The key uncertainties considered are the derating of generation technologies and the increase in electricity demand induced by the increase in temperature. The temperature increase constitutes the deep uncertainty in this analysis, although only its immediate impacts on the system are incorporated within the Exploratory Modelling analysis. For this purpose, this study used the assumed climate model of RCP 8.5 (Representative Concentration Pathway 8.5) derived by Aji et al. (2026). They used the global warming scenario of RCP 8.5 to estimate the derating potential of generation units and increases in temperature-driven demand. RCP 8.5 is a high-emission climate change scenario used by scientists to model future climate impacts (Hausfather, 2019).

Performance metrics are conventional indicators used by transmission system operators. The 10-year Electricity Business Plan specifies a minimum regional reserve margin target of 34%. Both the 10-year Electricity Business Plan and the 2060 Long Term Electricity Plan also emphasise emissions and (levelised) system costs as important metrics. Finally, the principal reliability metric, the number of lost load hours, quantifies the hours during which Calliope must utilise extremely high-cost lost load technology. This situation arises when all available transmission and generation capacity is fully exploited and demand nevertheless remains unmet.

The Exploratory Modelling and Analysis (EMA) Workbench tool was used to perform a systematic exploratory model analysis of uncertainties and system performance in a wide range of scenarios (Kwakkel et al., 2016). Subsequently, the experiments were executed using the DelftBlue High Performance Computing (HPC), due to the wish to simulate many simulations in a relatively short timeframe. In total, between 1000 and 1600 simulation runs were performed for each of the three years, with varying policies and associated scenarios evaluated per policy. Another advantage of employing HPC resources is that once a job has been submitted to the system, users are free to engage in other tasks while the computation proceeds autonomously. The resulting outcomes are presented and discussed in the following chapter.

4 Results

This chapter presents the results of the energy system modelling and the exploratory modelling analysis described in Chapter 3. Section 4.1 reports the Calliope optimisation results for the three planning horizons, assessing how the current plan performs in terms of adequacy, reserve margins, costs and emissions for 2034 (4.1.1), 2045 (4.1.2) and 2060 (4.1.3). Section 4.2 presents the results of the exploratory analysis, showing how deeply uncertain climate impacts affect robustness in 2034 (4.2.1), 2045 (4.2.2) and 2060 (4.2.3).

4.1. Calliope Energy System Modelling

The Calliope optimisation results for all three planning horizons are summarised in Table 4.1. The table reports annual electricity demand, levelised system costs, CO_2 intensity, total emissions, and hours of lost load for each modelled year. The 2034 results include both the base scenario and the Accelerated Renewable Energy Development (ARED) scenario, reflecting the two pathways defined in the 10-year Electricity Business Plan. This table forms the basis for the answer to sub-question 1.

Table 4.1: Optimisation results from the Calliope base and ARED model for the system performance metrics.

Year	Demand [TWh]	Costs [$/MWh]	CO_2 intensity [kg/MWh]	Total emissions [Mt]	Lost load [h]
2034 (Base)	524	78.98	533.17	304	0
2034 (ARED)	524	81.61	477.18	272	0
2045	1234	74.85	298.58	398	0
2060	1713	85.77	28.69	53	0

4.1.1. Baseline Performance of the 2034 Infrastructure Plan

Figure 4.1 shows the supergrid plan up to 2034, which includes the HVDC interconnection from Jawa to Sumatra. The line from Jawa to Bali is also part of the supergrid, but in the 10-year Electricity Business Plan it is noted as an AC connection. Table 4.1 presents the performance measures for 2034 for both the base scenario and the ARED scenario. As expected, total emissions and CO_2 intensity decrease in the ARED scenario due to its higher share of renewable energy. However, the differences between the two scenarios are minimal. System costs increase slightly in the ARED scenario, likely due to additional reliance on battery storage capacity, but again the margin is small. In both scenarios, no hours of resource inadequacy were recorded, indicating that the planned infrastructure is fit to meet demand in 2034.

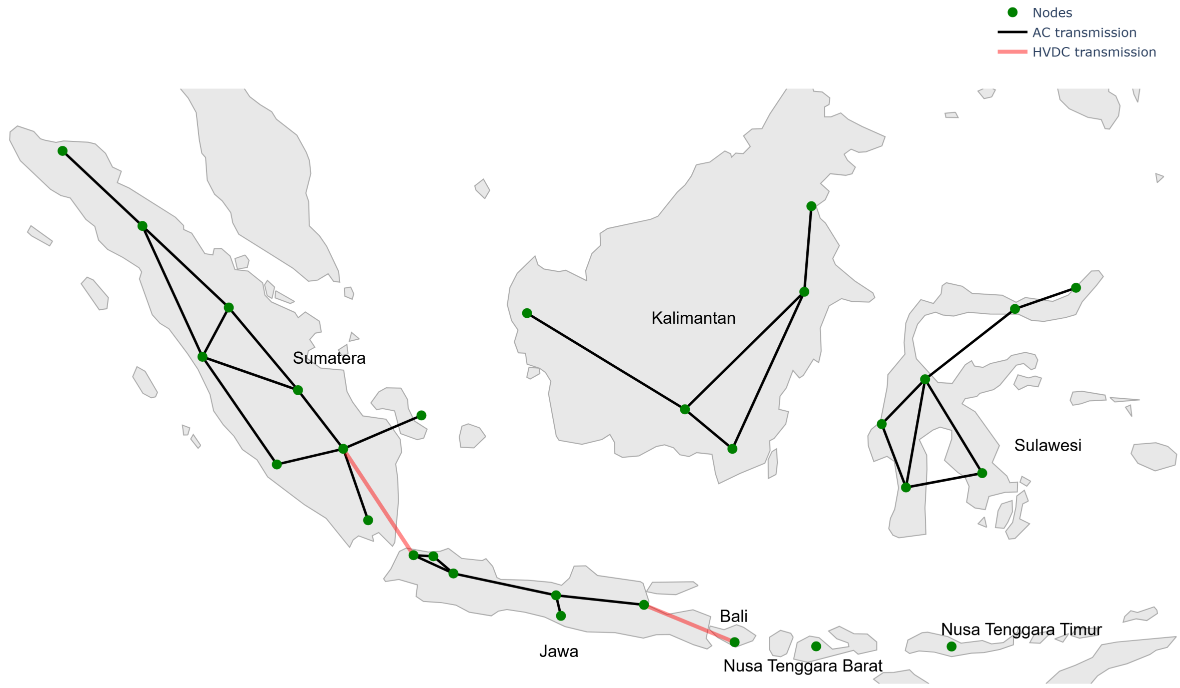

Figure 4.1: Calliope System Topology 2034

Figure 4.2 presents the reserve margins per region. The regional grouping follows the PT PLN system-province mapping. For connected provinces, it is assumed that they can jointly contribute to meeting peak demand. This is why the highly interconnected islands of Jawa and Sumatra are treated as a single system, whereas the islands of Nusa Tenggara are considered individually. Jawa's reserve margin is notably low, which is noteworthy given that it is by far the largest share of Indonesia's population and electricity demand. Most reserve margins in Sulawesi and Kalimantan fall between 20% and 50%, in general in line with the 10-year Electricity Business Plan objective of achieving a reserve margin of 34% in all provinces by 2034 (PT PLN, 2025b). It should also be noted that variable renewable energy sources are discounted in the calculation of the reserve margin and dispatchable sources are not (MEMR et al., 2024).

Some striking reserve margins are those of Kalimantan Barat, Nusa Tenggara Barat, and Nusa Tenggara Timur. Kalimantan Timur has its own reserve margin value because at the moment it is not yet connected to any other region, which means that it cannot draw on generation from neighbouring provinces during periods of shortfall. The high reserve margin of the Nusa Tenggara islands may be explained by the fact that they do not have AC capacity that could serve as a backup in the event of a generation capacity failure. In particular, the Nusa Tenggara islands have substantial solar capacity planned for 2060 due to their excellent capacity factors, and the long-term energy plan envisions them as a key supplier of renewable energy to the Jawa–Bali system (MEMR, 2025a).

Table 4.2: Regional reserve margins for 2034

Region	Reserve margin [%]
Sumatra	51.3
Jawa–Bali	21.0
Kalimantan Barat	96.3
Kalimantan Timur	35.1
Sulawesi Utara	41.1
Sulawesi Selatan	29.5
Nusa Tenggara Barat	70.4
Nusa Tenggara Timur	110.3

The load duration curves for the supergrid lines in the Appendix Figures A.2 and A.1 show line usage in the ARED scenario. Given the higher renewable share, this scenario places the greatest demand on interconnectors. Notably, for both the Sumatra–Jawa and Jawa–Bali connections, the maximum load on the line does not reach the line's maximum capacity, showing that the planned transmission capacity is more than adequate for 2034 conditions.

4.1.2. Baseline Performance of the 2045 Infrastructure Plan

Table 4.1 presents the Calliope optimisation results for 2045. The increased deployment of cheap renewable energy sources drives both the system costs and CO_2 intensity downward compared to 2034. However, as the total electricity demand continues to grow, absolute emissions rise in relation to 2034 despite the lower carbon intensity. The model reports zero hours of lost load, indicating that the planned infrastructure remains sufficient to meet demand under the 2045 conditions.

Figure 4.2 shows the expansion of the planned supergrid lines by 2045. The addition of HVDC connections linking Kalimantan to Sulawesi and Sulawesi to the Jawa–Bali to Nusa Tenggara corridor creates a roughly square structure spanning the major island systems. This topology is significant because it allows power to be drawn from two sides of the country simultaneously, improving both flexibility and resilience. The renewable-rich regions of Kalimantan and Nusa Tenggara can now supply deficit areas such as Jawa–Bali through multiple pathways, reducing dependence on any single interconnector.

Table 4.3 indicates that the reserve margin in Sumatra has declined substantially compared to 2034, while the margin in Jawa–Bali has even fallen below zero. The higher reserve margins in Kalimantan Timur and on the Nusa Tenggara islands are the result of large-scale additions of hydroelectric and solar power, respectively (MEMR, 2025a). This suggests that by 2045 and under the planned generation expansion of the 2060 Long-Term Electricity Plan, the system becomes highly dependent on these two corridors to supply Jawa's high-demand nodes. Thus, although the renewable capacity in the system increases, a new vulnerability is simultaneously introduced in these two transmission lines.

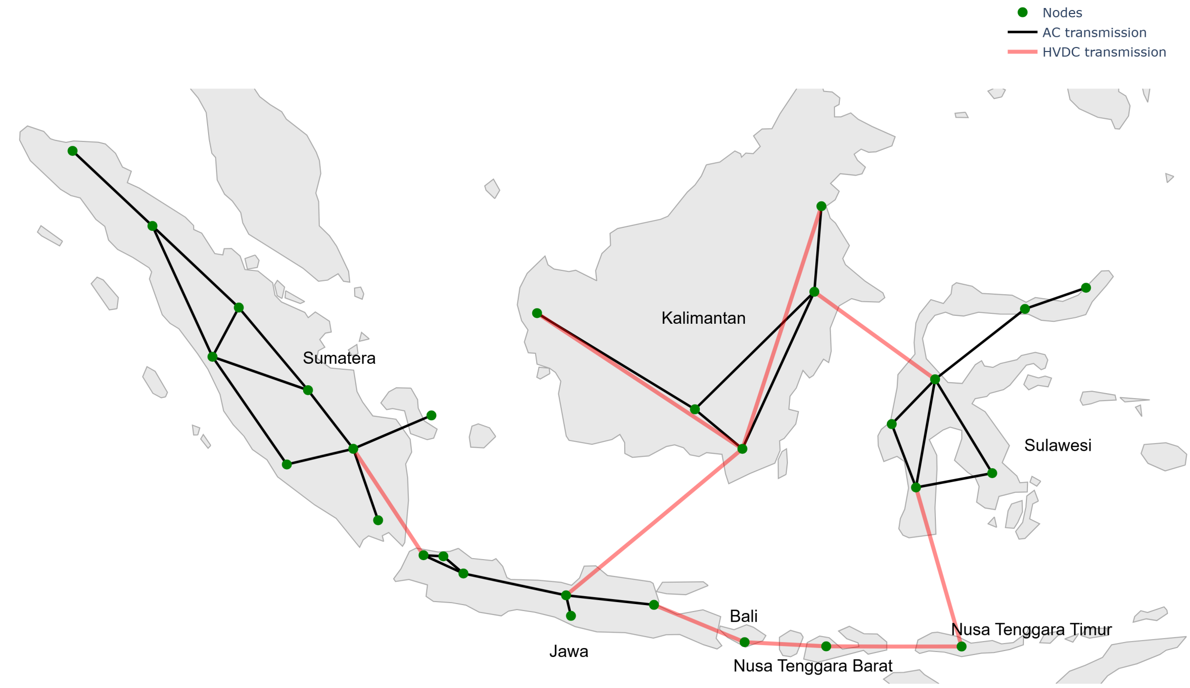

Figure 4.2: Calliope System Topology 2045

Table 4.3: Regional reserve margins for 2045

Region	Reserve margin [%]
Sumatra	16.0
Jawa–Bali	-19.3
Kalimantan Barat	28.7
Kalimantan Timur	93.3
Sulawesi Utara	22.6
Sulawesi Selatan	3.3
Nusa Tenggara Barat	186.3
Nusa Tenggara Timur	100.2

4.1.3. Baseline Performance of the 2060 Infrastructure Plan

Table 4.1 shows the Calliope optimisation results for 2060. Although Table A.3 indicates that costs generally fall due to learning effects, total system costs increase. This is mainly driven by the deployment of 100% hydrogen co-fire in former CCGT plants, 100% ammonia (NH_3) co-fire in repurposed coal units and Carbon Capture and Storage (or CCS) in both. Green hydrogen and ammonia are predicted to be much more expensive than present-day natural gas and coal (Silalahi et al., 2023; Tjahjono et al., 2023). At the same time, large expansions in renewables, CCS, and cross-border interconnection (Figure 4.3) sharply reduce the intensity of CO_2 from electricity generation and total emissions. Despite these changes and higher costs, the model still reports zero hours of lost load, indicating that the 2060 plan is adequate under the baseline assumptions.

Table 4.4 again shows increases in the regional reserve margins in Nusa Tenggara and Kalimantan Timur, driven by the planned addition of solar capacity in Nusa Tenggara and the significant deployment of hydropower in Kalimantan. These high regional surpluses offset the low and negative margins in the Sulawesi Selatan and the Jawa–Bali system, which together represent the highest concentration of electricity demand in Indonesia. The planned supergrid interconnections are therefore essential to enable these surplus regions to supply the deficit areas by 2060. For such a structural dependency towards 2060, it is important that it is robust against as many different plausible futures as possible.

For decision makers, this result matters because it confirms that the model behaves as expected. The optimisation reproduces that expected reliability outcome of the planners. It can now be used to question the plan under deeply uncertain climate change effects.

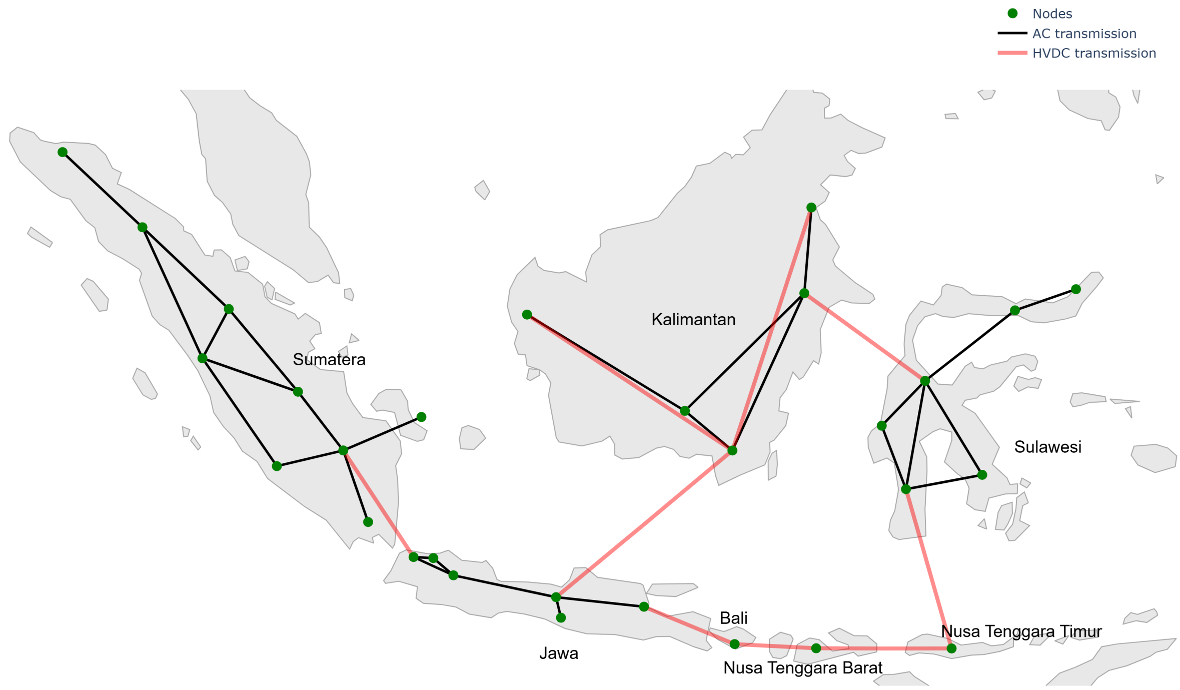

Figure 4.3: Calliope System Topology 2060

Table 4.4: Regional reserve margins for 2060

Region	Reserve margin [%]
Sumatra	13.7
Jawa–Bali	-24.0
Kalimantan Barat	44.7
Kalimantan Timur	109.9
Sulawesi Utara	1.8
Sulawesi Selatan	-18.5
Nusa Tenggara Barat	208.9
Nusa Tenggara Timur	220.1

4.2. Exploratory Analysis

This section presents the results of the Exploratory Modelling (EM) analysis, conducted using the EMA Workbench on DelftBlue. The analysis stress-tests the infrastructure plans identified in Section 4.1 against combinations of two key climate uncertainties: temperature-driven demand increases and generation derating. The results are reported separately for the three planning horizons. Section 4.2.1 examines whether these deeply uncertain effects of climate change can cause a loss of load in various scenarios for 2034. Section 4.2.2 does the same for 2045 and identifies critical interconnection levers. It does so after applying a directed search to find robust candidate strategies. Section 4.2.3 does the same for 2060 and identifies a key bottleneck for robustness in the system.

4.2.1. Exploratory Analysis 2034: Robust Performance Across All Scenarios

Figure 4.4 presents the performance of the 2034 system under the two climate uncertainties, with all policies considered together. Under the supergrid plan, two supergrid connections are expected to be in place by 2034. One will link Bali with Jawa Timur (Bali-Jatim), the easternmost province of Java, and the other will connect Banten with Sumatra Selatan (Banten-Sumsel), thus linking southern Sumatra to western Java (MEMR, 2025a). Figure 4.4 shows that, under no tested policy and in none of the climate scenarios tested, the system ever experienced more than 8 hours of lost load. Although this study simulates approximately four weeks (focusing on the most critical weeks), the same benchmark is used as a conservative screening criterion for adequacy. This means that even under the most extreme effects of climate change represented in the scenarios (increased demand and degraded capacity due to increasing temperatures), the system remains functional and can deliver the required load at all nodes. Even the version of long-term planning without interconnection capacity between Sumatra and Jawa and minimal capacity between Bali and Jawa shows no lost load hours and would form a robust infrastructure against the effects of climate change.

The 8-hour threshold is adopted as the adequacy criterion for two main reasons. First, the historical System Average Interruption Duration Index (SAIDI) is 8.2 hours of lost load per year (MEMR, 2024). Designing a future grid that is less reliable than the current one is politically and socio-economically difficult to justify. Second, as a rapidly developing economy, Indonesia aims to have a highly reliable power system. For that reason, this study aligns its reliability benchmark with that used in several Western European countries (NYSRC, 2020). However, currently Indonesia applies a 1-day-per-year Loss of Load Expectation criterion for system planning (PT PLN, 2025a). Therefore, in sections 4.2.2 and 4.2.3, the 8-hour SAIDI-based standard is explicitly compared with the 1-day-per-year LOLE standard.

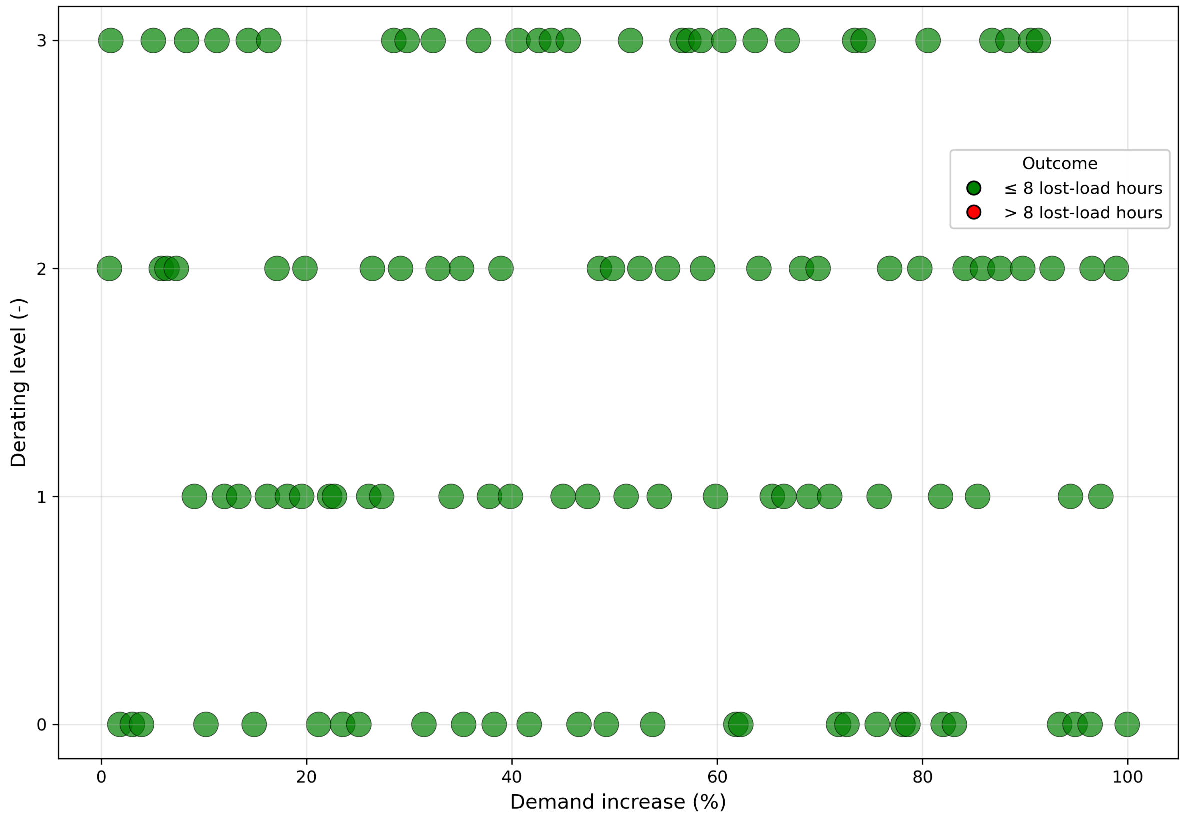

Figure 4.4: Exploratory analysis results of all tested 2034 policies showing that no climate-stress scenario crosses the reliability threshold.

Zooming in on the performance of the individual policies, Figure 4.5 shows the performance of the individual policies tested. The entire 2034 policy set is also listed in the Appendix Table A.15. At the moment there is already a connection between Jawa Timur and Bali. This is an AC connection, for which an increase in capacity is planned. The other connections, such as the one between Banten and Sumatra Selatan, are intended to be HVDC (MEMR, 2025a; PT PLN, 2025a). The plausible ranges of these two future supergrid lines were divided into 3 categories and then all combinations were tested, resulting in 9 possible policies. On the x-axis of each policy square, the demand increase is plotted and on the y-axis of the derating level. The colour in the squares shows which share of the scenarios within that combination of derating and demand increase resulted in less than 8 lost load hours for that specific scenario. As said before, for 2034 there were no instances of that. The Low Bali-Jatim, no Banten-Sumsel policy performs equally well as the High Bali-Jatim, high Banten-Sumsel policy. This suggests that the minimally planned transmission capacity is sufficient by 2034, which is important due to the capital-intensive nature of expanding transmission capacity.

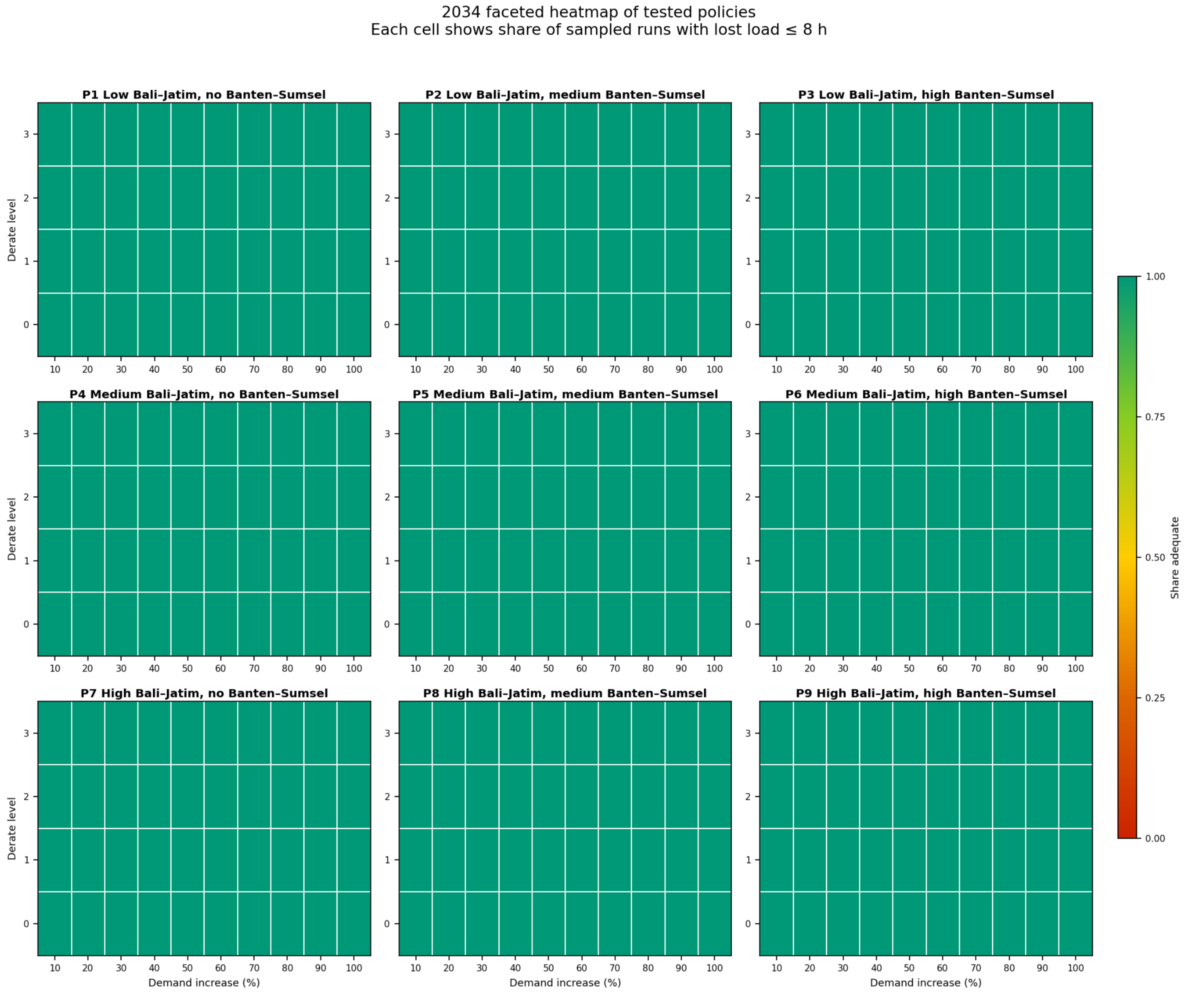

Figure 4.5: Robustness of the tested policies for 2034 under different demand increases and derating levels.

For evaluating the remaining previously identified performance metrics, the feature scoring table is appropriate. The feature scoring table in 4.6 shows importance scores, which indicate how strongly each variable explains the variation in the results between experiments. For example, approximately 51% of the variation in 2034 CO_2 emissions between scenarios and policy levers is explained by changes in the Banten–Sumatra Selatan HVDC capacity, connecting the islands of Jawa and Sumatra. Because renewable generation is the cheapest in Calliope, it is dispatched first, similar to marginal pricing markets. The HVDC connection enables renewable power to be transmitted from the generation sites to the demand centres. The same HVDC line also strongly affects the levelised carbon intensity (kg CO_2 per kWh). Interestingly, the Jawa–Bali connection has a negligible impact on all outcomes of interest. In addition, scenarios with higher demand explain some of the remaining CO_2 variation, likely because cheap capacity is exhausted and more expensive generation must be used.

In the 2034 scenarios, reserve margins are mainly affected by capacity derating and higher demand. The policy levers have negligible impact. This is expected as the reserve margin is based on the total generation capacity and the peak demand. Up to 78% of the variation in the reserve margin of Kalimantan Barat and more than 80% in northern Sulawesi's can be explained by derating levels.

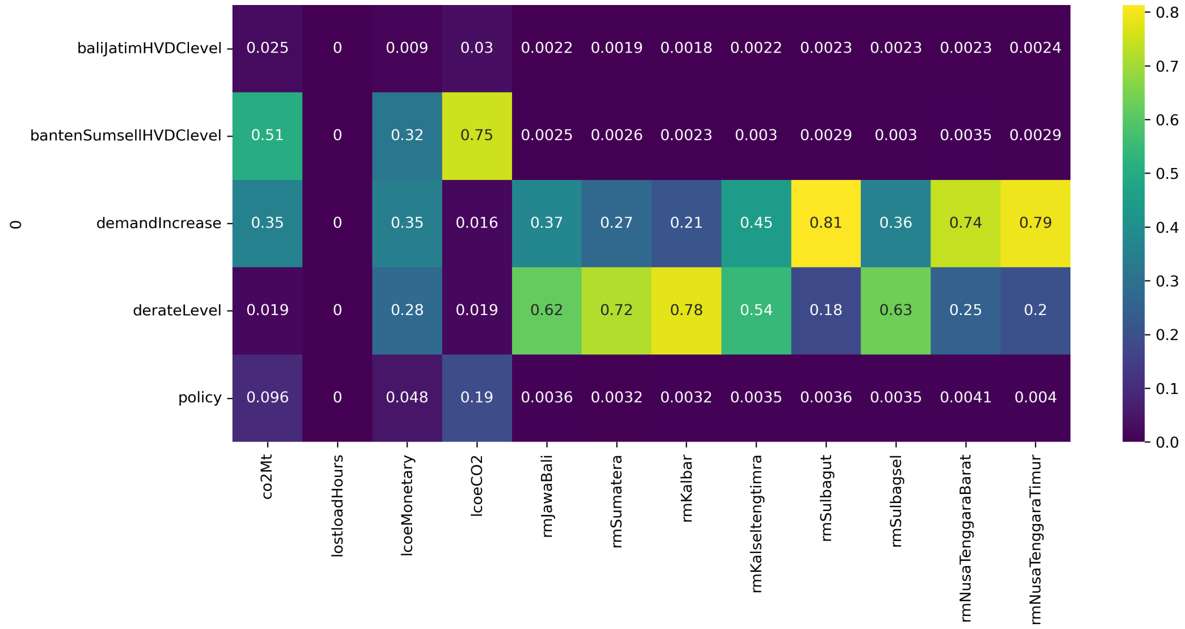

Figure 4.6: Feature scoring results table for the 2034 exploratory analysis

4.2.2. Exploratory Analysis 2045: The Bali–NTB Link as Critical Enabler

The EM analysis for 2045 began with a directed search to identify candidate strategies. The directed search functionality uses the epsilon-NSGAII algorithm to explore the lever space. The lever space consisted of seven levels of HVDC interconnectors in a single fixed reference scenario, to identify Pareto-efficient candidate strategies (Kwakkel, 2023a). The algorithm evaluates different lever combinations for a specified number of function evaluations (nfe's). A limit of 8 lost load hours was imposed, meaning that any candidate strategy had to remain below this 8 lost load hours threshold. Solutions were required to simultaneously minimise emissions and levelised costs. In the 2045 directed search, uncertainties were not sampled but held constant. A modest 2% increase in demand was assumed and the minimum derating level was set in the reference scenario, to filter out strategies that would only be adequate in the specific scenario used for the optimisation, see Table A.7. The directed search was executed multiple times using different seed values, and the resulting Pareto fronts were combined. This is standard practice, as epsilon-NSGAII is a stochastic algorithm and a single execution may not capture all parts of the Pareto front (Kwakkel, 2023a). Figure A.3 shows that after 1000 evaluations, epsilon performance no longer increases, indicating stable candidate solutions. After merging the seeds, the directed search resulted in four candidate strategies with varying levels of capacity (Table A.8). The candidate strategies identified in this step and others were subsequently stress-tested in a wide range of uncertainty scenarios in a follow-up run on DelftBlue.

The results of the EM analysis are presented in Figure 4.7, where all policies are still displayed together. What stands out is that, unlike in 2034, there are scenarios in 2045 in which the lost load exceeds the permitted threshold, indicating that the plan is not robust against this particular combination of demand growth and derating. Figure 4.7 shows that this occurs most frequently on the right side of the graph, where both the derating and the increase in demand are moderate to high. This illustrates that there is a limit to what the system can handle. At the same time, some policies remain robust across the entire range of uncertainties. For this reason, the policies are now examined individually.

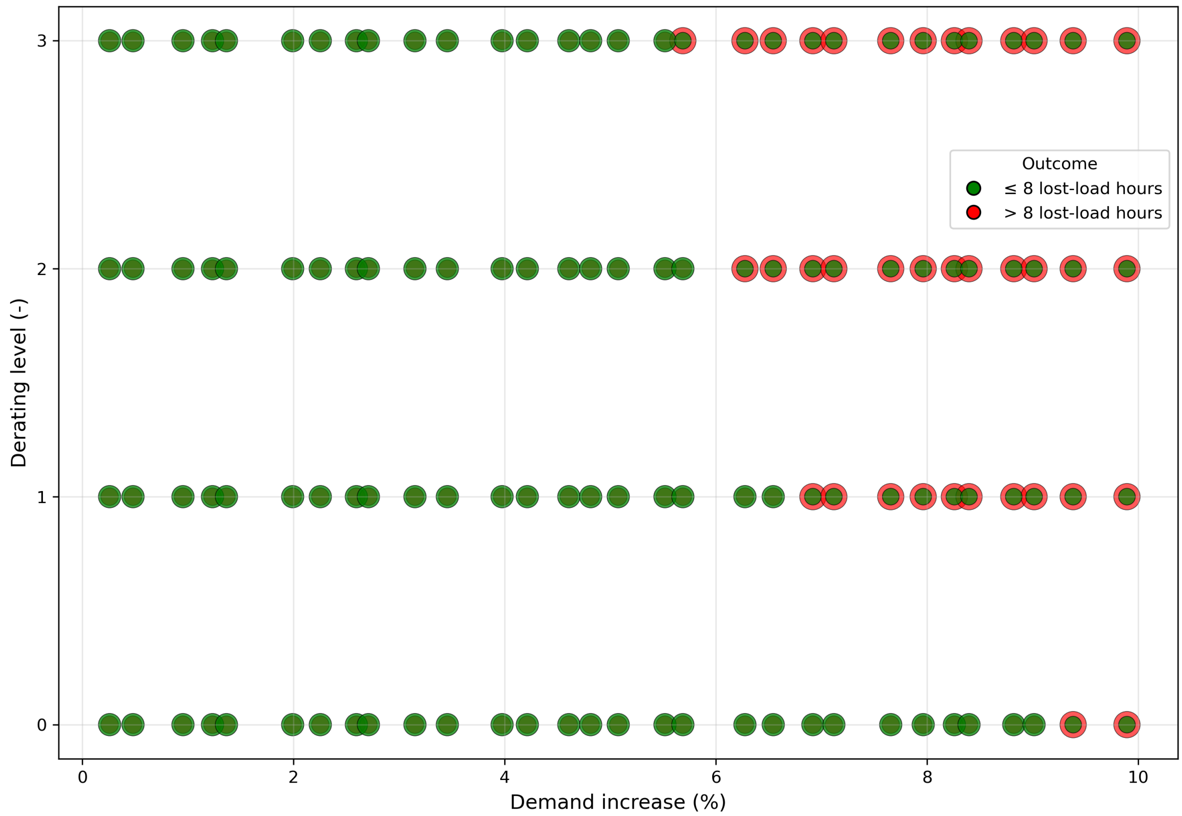

Figure 4.7: Exploratory analysis results of all tested 2045 policies together showing some policies fail under moderate to high climate stress.

Nine 2045 policies were stress-tested under 30 sampled demand increases from 0–10% using Latin Hypercube Sampling, combined with four derating levels. The policies included the four 2045 directed-search candidates, minimum- and maximum-capacity strategies, two 2060 directed-search candidates, and a backbone-only strategy (see Subsection 4.2.3). The entire 2045 policy set is listed in the Appendix Table A.16. Their performance can be seen in Figure 4.8. Policies can be distinguished in inadequate, partially robust, and fully robust policies. Policy 1, the minimum capacity possible, and 7 never meet the adequacy criterion in any of the 120 scenarios. They differ from the other 7 strategies tested on one key point. Both keep the Bali–Nusa Tenggara Barat interconnector at its 1000 MW minimum, resulting in the line being saturated for almost the entire month. This low interconnection capacity causes most of the lost load hours to occur in Bali.

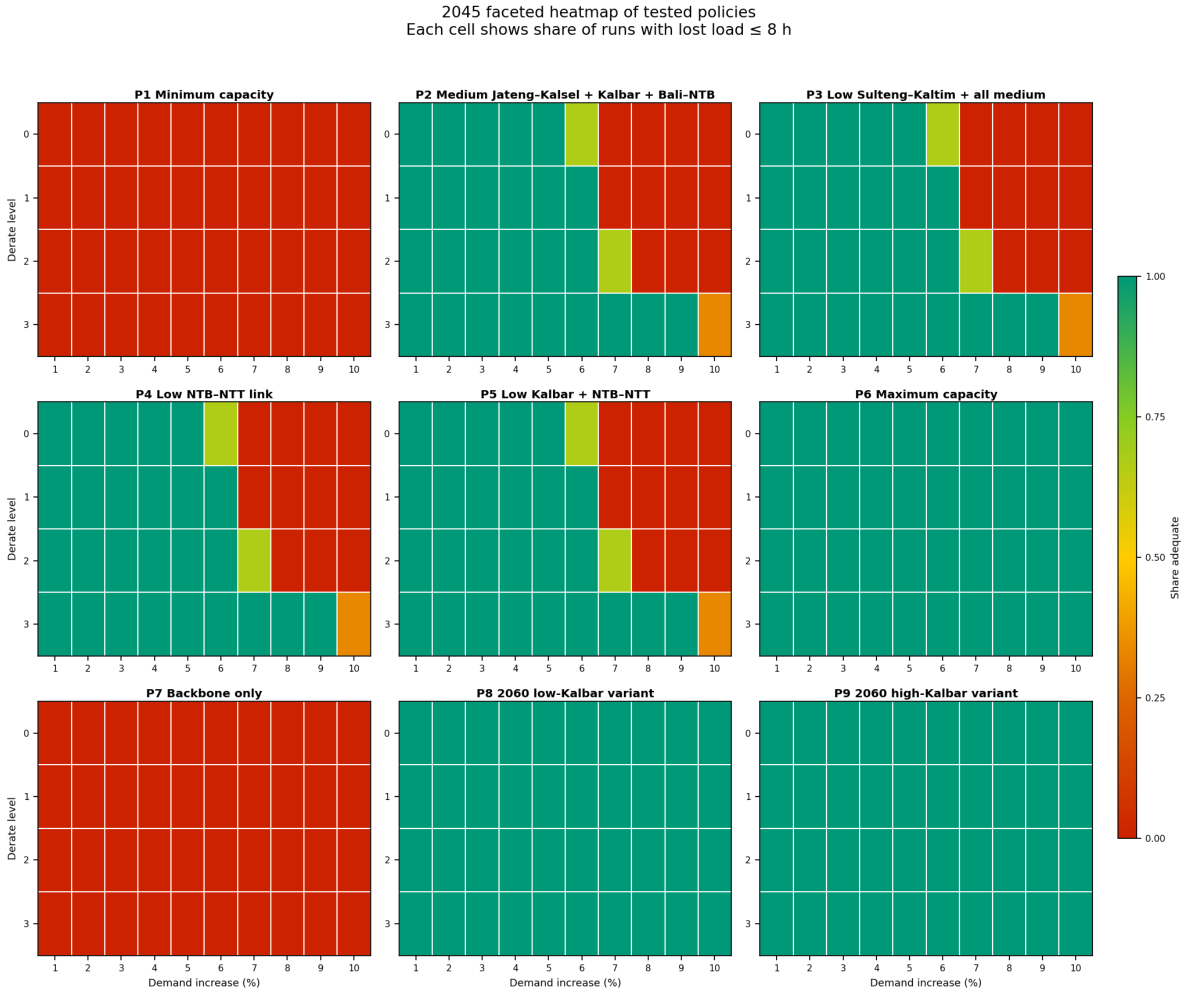

Figure 4.8: Robustness of the tested policies for 2045 under different demand increases and derating levels.

The four candidate strategies, 2 through 5, have identical lost load hours. Under severe derating, they accommodate demand increases of up to 5.5%. Without derating, up to 9.0%. Thus, the directed search found solutions more robust than the minimum-capacity and backbone-only strategies. However, adequacy still declines when high derating coincides with strong demand growth. Emissions and levelised cost differences when only looking at the successful runs (so less than 8 LLH's) are negligible.

Three policies remain robust against the entire range of uncertainties. The maximum-capacity strategy (policy 6) and the two directed-search strategies targeting 2060 (policies 8 and 9). All meet the adequacy criterion in all 120 scenarios, including the combination of maximum derating and maximum demand growth. This is not unexpected, because the directed search for 2060 is already identifying candidate strategies capable of operating that system while keeping lost load below 8 hours. By 2060, there is less dispatchable capacity and more variable generation, and, as shown in 4.1.3, the system is even more reliant on the supergrid. The 2045 stress test identifies the Bali–Nusa Tenggara Barat connection as the key enabling link. Keeping this interconnector at minimum capacity causes inadequacy, while raising it to at least the intermediate level greatly improves performance. However, full robustness under the climate uncertainties for 2045 still requires measures beyond the 2045 directed-search strategies, which fail under sufficiently extreme derating and demand growth. The strategies found via the directed search for 2060 are adequate, but this would mean building overcapacity by 2045, to be ready for 2060.

The feature scoring table in Figure 4.9 shows the importance scores of the stress test for 2045. It shows that the increase in demand is the main driver behind the increase or decrease in CO_2 emissions. It also shows that, as in 2034, the effects of climate change heavily impact the reserve margins of the different regions. Finally, it shows that the Bali to NTB and Jawa Tengah to Kalimantan Selatan HVDC lines affect the lost load hours, enabling the transfer of capacity to where its needed and levelised costs, allowing renewables to be spread across the system.

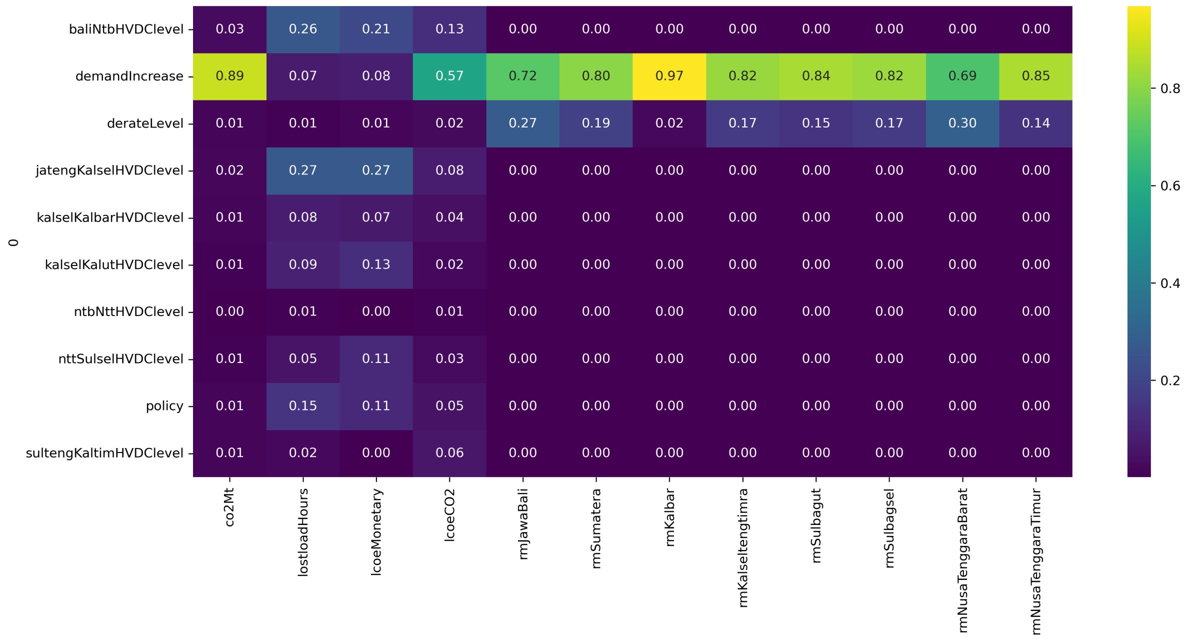

Figure 4.9: Feature scoring results table for the 2045 exploratory analysis.

However, the general feature scoring table is based on the raw outcome values (Kwakkel, 2023b). It therefore shows which inputs are important for explaining variation in outcomes, but it does not directly answer which inputs are most important for keeping the system within the accepted adequacy threshold. For that reason, an additional binary classification was performed. Model runs were classified as successful when lost-load hours remained below the 8-hour benchmark and unsuccessful when they exceeded this benchmark. Extra Trees was used as the classification algorithm to calculate the corresponding feature scores. This algorithm is suitable for this purpose because it builds an ensemble of randomised decision trees and combines their results, helping to reduce the instability of individual trees while remaining computationally efficient (Geurts et al., 2006). The results, shown in Table 4.5, confirm the critical role of the Bali–Nusa Tenggara Barat HVDC line in determining whether the 2045 system remains within the lost-load threshold.

Table 4.5: Relative importance scores for staying under relability treshold by 2045.

Variable	Importance
Bali – Nusa Tenggara Barat HVDC level	0.52
Jawa Tengah – Kalimantan Selatan HVDC level	0.16
Kalimantan Selatan – Kalimantan Barat HVDC level	0.13
Sulawesi Tengah – Kalimantan Timur HVDC level	0.09
Nusa Tenggara Timur – Sulawesi Selatan HVDC level	0.05
Kalimantan Selatan – Kalimantan Utara HVDC level	0.03
Nusa Tenggara Barat – Nusa Tenggara Timur HVDC level	0.01
Demand increase	0.00
Derate level	0.00

Finally, the two reliability thresholds are compared. Up to this point, the 8-hour threshold has been used. Figure 4.10 presents the results of the same analysis conducted using the 24-hour standard.

When the directed search was repeated, the same candidate strategies were identified. The only change made was to increase the adequacy criterium from a maximum of 8 lost load hours per year to 24. Compared to Figure 4.7, the system shows greater robustness to the deeply uncertain impacts of climate change. System failure now occurs only under scenarios with extremely high demand growth and severe derating, which is the case in the upper-right region of the scenario space. Under this criterion, the associated infrastructure planning approach appears considerably more robust than when using the 8 hour threshold.

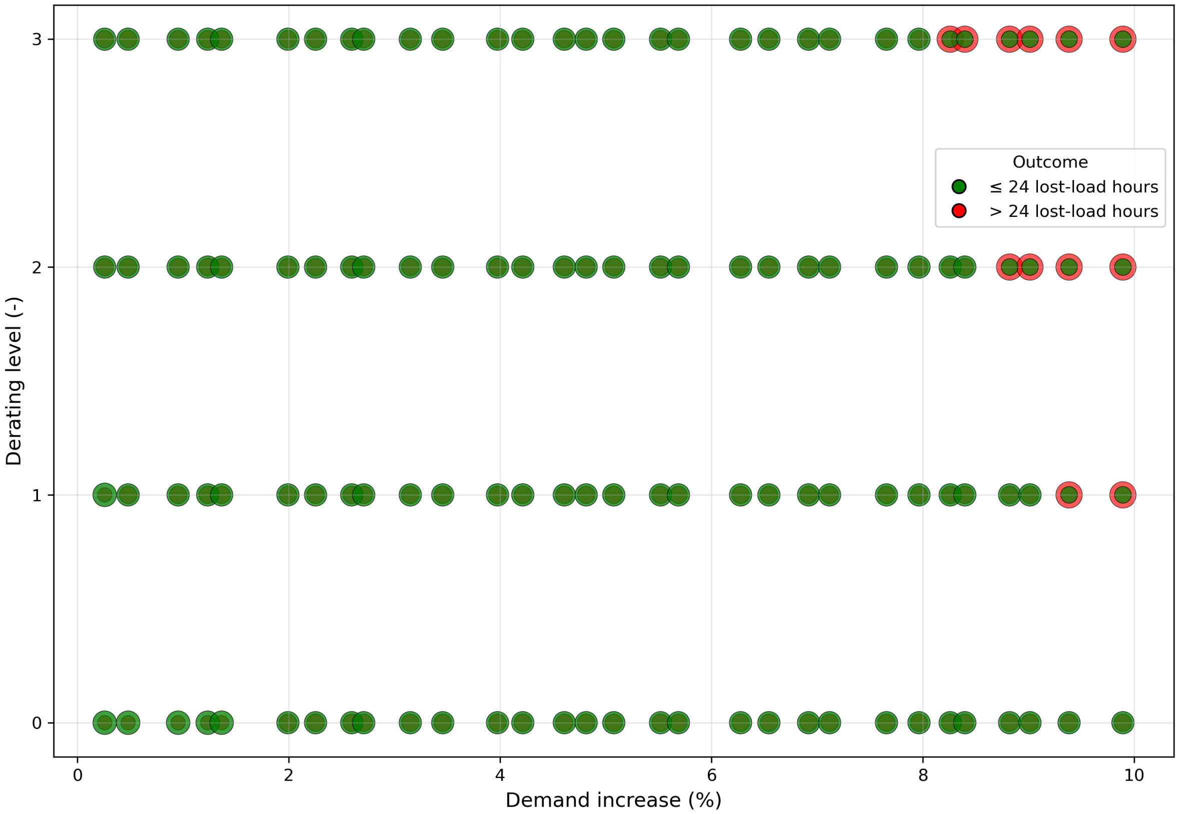

Figure 4.10: Exploratory analysis results of all tested 2045 policies together for the 24 hour reliability threshold.

4.2.3. Exploratory Analysis 2060: Climate Uncertainty Dominates System Adequacy

A directed search was conducted for 2060 to identify candidate policies. After introducing fixed climate stress, the analysis was performed for five seeds and the results were merged to eliminate strategies that recurring across seeds. After about 1000 evaluations, the progress of the epsilon became minimal, indicating stable candidate strategies (Figure A.4). This yielded two final strategies, see Table A.10 in the Appendix. In both strategies, three HVDC lines were set at their maximum feasible capacity. Because the influence of the remaining lines was not yet established at this stage, these three maximum-capacity lines are referred to as the "backbone" of the strategy.

For the 2060 stress test, the policy set included a minimum-capacity strategy, a maximum-capacity strategy, a backbone-only strategy, and the directed-search candidates. In addition, eight factorial-design policies were added to test the influence of the four remaining secondary levers besides the backbone connections; see Appendix A.8. The entire 2060 policy set is listed in the Appendix Table A.17. For each strategy, 30 LHS demand increase scenarios were sampled over the 4 derating levels. This resulted in 1560 total runs. Table A.11 shows a complete overview of the levers and uncertainties for 2060.

The results of the stress test results for 2060 are presented in Figure 4.11. The x-axis shows increasing demand, and the y-axis shows increasing derating. By 2060, only those scenarios that combine low derating levels (0–1) with modest demand growth (roughly below 1 to 2%) consistently meet the 8-hour lost-load threshold, appearing as the cluster of green dots in the lower-left corner of the figure. As either stressor intensifies, the adequacy effectively disappears. Under the combined effect of even a moderate amount of demand increase and derating, the middle and right areas of the graph show universal failure across all 13 policies, dominated by red dots. This indicates that by 2060 no individual policy can ensure robust adequacy under even minimal uncertainty due to climate change effects.

Figure 4.11: Exploratory analysis results of all tested 2060 policies together showing that adequacy is achieved only under minimum climate change uncertainty.

When examining the performance of individual policies, another notable pattern emerges, see Figure 4.12. They can be classified as partially successful or never successful. The partially successful policies show broadly similar performance across the different scenarios. This suggests that simply adding more transmission capacity, or "gold-plating" the grid, does not necessarily improve the robustness of the system. Policy 13, which represents the maximum-capacity configuration, performs no better than the other partially successful policies. Figure 4.12 also shows that the minimum-capacity strategy (Policy 1), the backbone-only strategy (Policy 2), and Policies 5 and 8 never meet the reliability criterion. A key difference between these strategies and the successful strategies is that the unsuccessful strategies never set the Bali–Nusa Tenggara Barat interconnector above its 1000 MW minimum. Together with the 2045 results, these findings suggest that the effective backbone also includes the Bali–Nusa Tenggara Barat line, set one level below its maximum capacity. The final backbone is:

From	**To**	**Capacity**
Jawa Tengah	Kalimantan Selatan	26 GW
Kalimantan Selatan	Kalimantan Utara	15 GW
Nusa Tenggara Timur	Sulawesi Selatan	4 GW
Bali	Nusa Tenggara Barat	$\geq$ 7.5 GW

Figure 4.13 shows the importance scores for the 2060 stress test. Two patterns stand out. The HVDC levers determine a large part in the variation of levelised costs, with three levers determining more than 80% of the variation. The increase in demand and derating dominate the emissions, together explaining most of the variation in the CO2Mt metric. Among policy levers, the most important for lost-load hours is the Bali–Nusa Tenggara Barat connection (baliNtbHVDClevel ≈ 0.55).

However, feature scoring techniques use the raw values of the outcomes (Kwakkel, 2023b). In addition, it is relevant to identify which parameters are most important to keep lost load hours below the 8-hour benchmark. This is a binary classification problem, therefore the extra-trees feature scoring was applied using a binary classification of success, defined as fewer than 8 lost load hours. The result of this analysis is shown in Table 4.6. The table indicates that the two effects of climate change are the dominant factors in determining whether the system remains below 8 lost load hours.

Table 4.6: Relative importance of uncertainties and levers for staying below 8 lost load hours

Variable	**Importance**
Demand increase	0.55
Derate level	0.25
Bali – Nusa Tenggara Barat HVDC level	0.13
Sulawesi Tengah – Kalimantan Timur HVDC level	0.02
Nusa Tenggara Barat – Nusa Tenggara Timur HVDC level	0.02
Kalimantan Selatan – Kalimantan Barat HVDC level	0.01
Nusa Tenggara Timur – Sulawesi Selatan HVDC level	0.01
Jawa Tengah – Kalimantan Selatan HVDC level	0.01
Kalimantan Selatan – Kalimantan Utara HVDC level	0.01

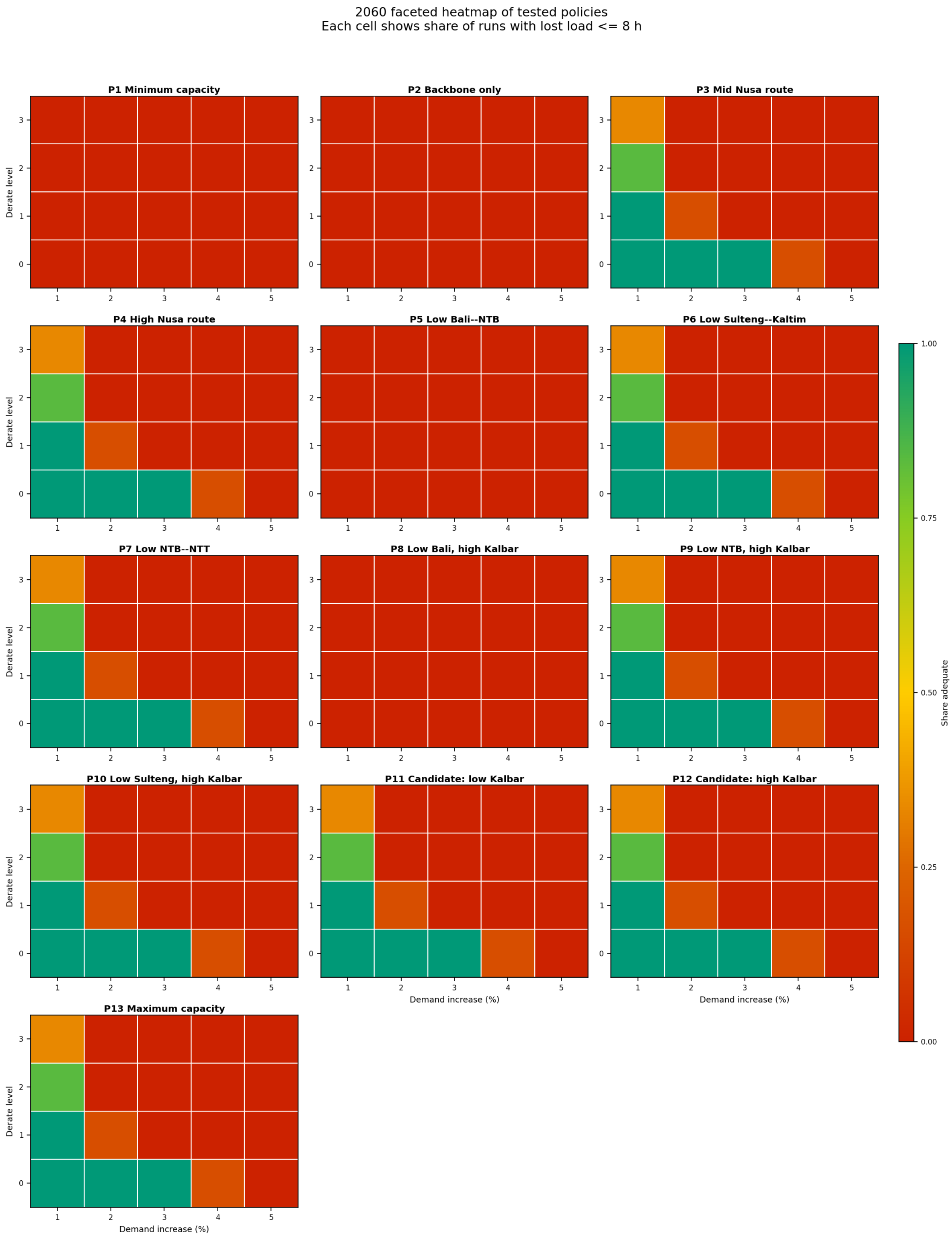

Figure 4.12: Robustness of the tested policies for 2060 under different demand increases and derating levels

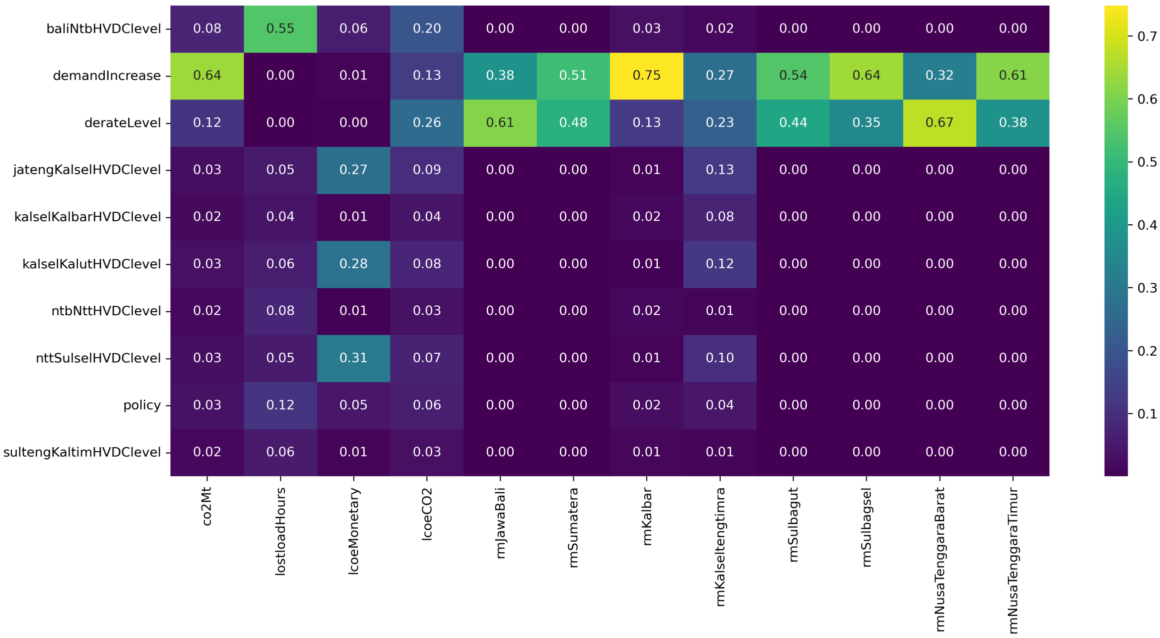

Figure 4.13: Feature scoring results table for the 2060 exploratory analysis.

Indonesia's current planning practice is based on a 24 hours loss of load reliability standard, while this study applies the stricter 8-hour benchmark motivated in Section 4.2.1. Applying the 24-hour standard substantially changes the interpretation of the 2060 results. Figure 4.14 is much more optimistic than the corresponding 8-hour results in Figures 4.11 and 4.12. Under the 24-hour threshold, most of the scenario space remains adequate, and failures occur primarily in the upper-right corner where high demand growth coincides with severe derating (and only for a subset of policies). This contrast underscores how strongly results about long-term planning depend on the chosen reliability standard.

Figure 4.14: Exploratory analysis results of 2060 policies under the 24 hour lost load reliability treshold.

The initial 2060 stress test showed that the lost load was highly concentrated in the Jawa–Bali system, with Bali and Jawa Timur accounting for the largest share. In the weaker policies, the lost load was dominated by Bali, while in the stronger policies the remaining lost load became concentrated mainly in Jawa Timur. For these stronger policies, a large share of the lost load in Jawa Timur coincided with the hours in which the two adjacent transmission lines operated at or near their maximum capacity. One of these is the fixed Bali to Jawa Timur line, whose capacity was based on the 10-year Electricity Business Plan policy document. Diagnostics showed that this line was saturated for a very large part of the simulated month. This suggested that the fixed capacity of this connection might be an important bottleneck under higher demand and stronger derating, which motivated an additional stress test in which the Bali to Jawa Timur line capacity was increased from 2100 MW to 7500 MW.

Figure 4.15 shows the performance of all policies with increased capacity from Bali to Jawa Timur. With this added capacity, the system is robust to almost the entire range of climate change effects considered. Only the top-right corner, with both high demand growth and high derating, still causes failure.

Figure 4.16 shows that the policies that were never successful before also fail now. However, performance among the partially robust policies now differs clearly. Policies 7 and 13 perform best and identically. Policy 13 uses the maximum possible capacity, so its strong performance is expected. More interestingly, Policy 7 performs equally well despite including some low and even minimal-capacity supergrid lines (see Appendix A.14). This grid configuration is therefore much cheaper to build than the maximum-capacity one.

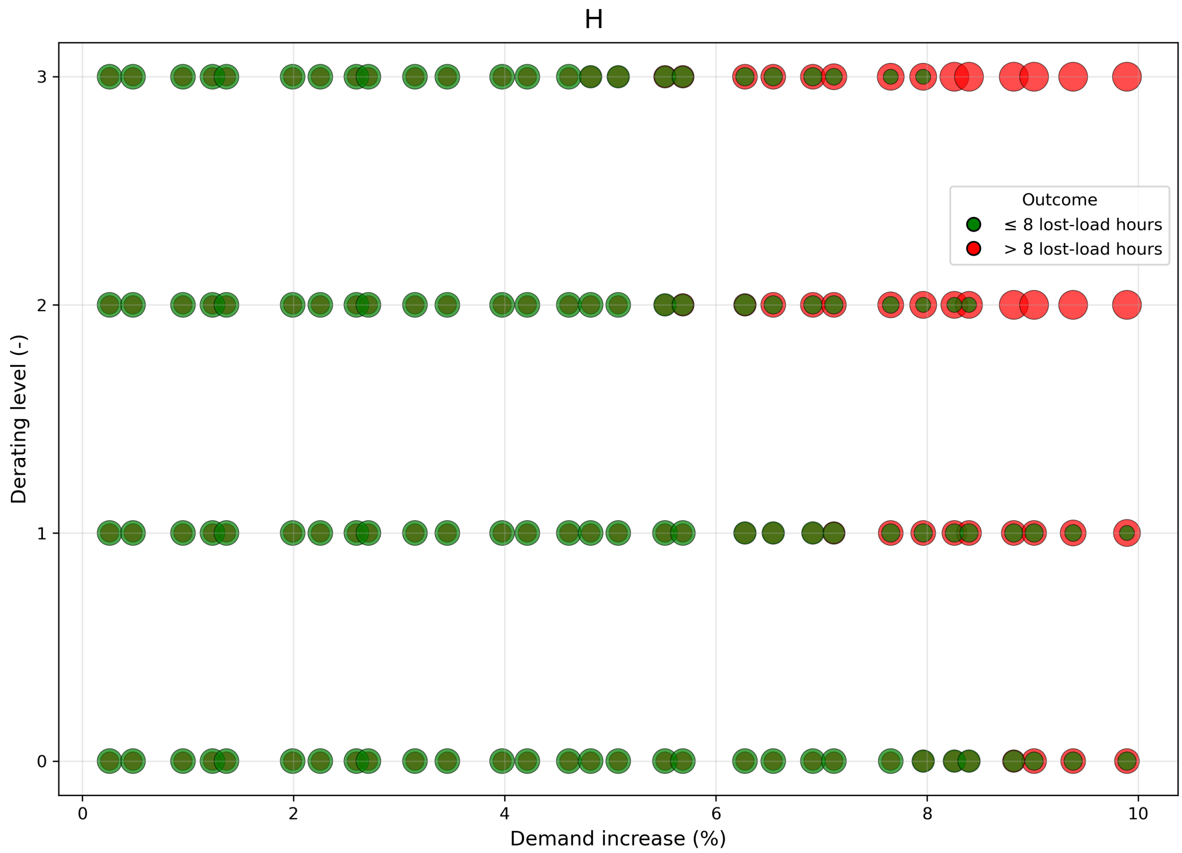

Figure 4.15: Exploratory analysis results of 2060 policies with reinforced Jawa Timur to Bali line and 8 hour reliability treshold showing a much more robust system.

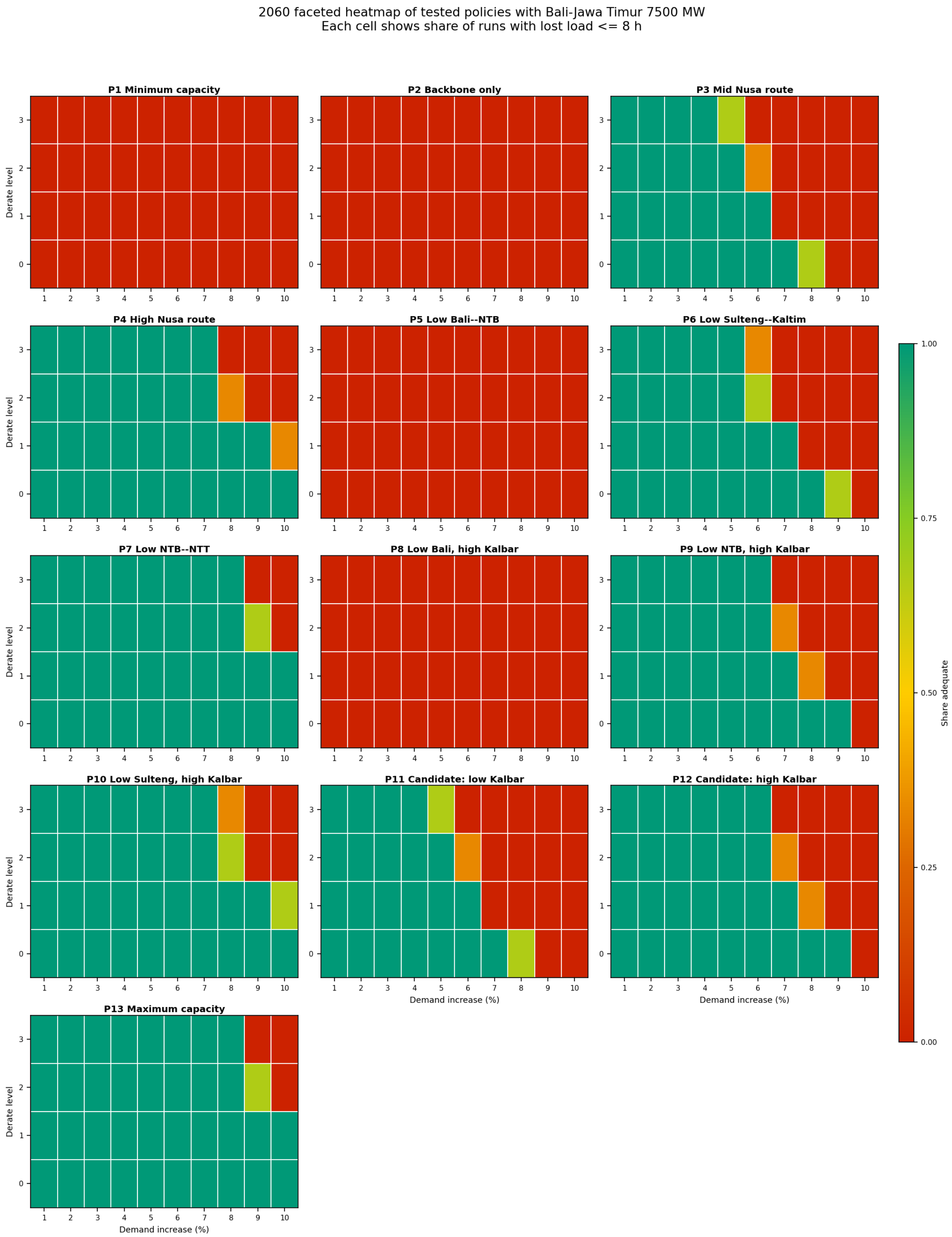

Figure 4.16: Robustness per 2060 policy with reinforced Jawa Timur to Bali connection.

When zooming out, there is a clear development visible over the three investigated years. In 2034, the infrastructure plan remains robust across the full tested uncertainty space, even under high demand increase and high derating. By 2045, vulnerabilities start to appear. Not all policies remain robust against the deeply uncertain effects of climate change. These vulnerabilities are concentrated in specific combinations of high climate stress and insufficient interconnection capacity, especially around the Bali–Nusa Tenggara Barat link. By 2060, the effect of climate uncertainty will become much stronger. The increase in demand and derating becomes more important than the capacity of any single supergrid link in determining whether the system remains below the threshold of 8 lost-load hours. Although some policies still achieve successful runs, they only do so in a limited number of scenarios, and performance becomes less clearly dependent on the selected policy. Diagnostics showing where lost load occurs indicate that the Jawa Timur to Bali connection, whose capacity is fixed in the 10-Year Electricity Business Plan (RUPTL), forms a critical bottleneck.

After the Jawa Timur to Bali link was reinforced and the simulation was repeated, the system became substantially more robust than before, although vulnerabilities still appeared under more severe climate stress. Policy 13 and Policy 7 perform equally well. This suggests that maximising all supergrid capacities does not necessarily lead to a more robust grid. Instead, the results indicate that Indonesia's long-term power infrastructure plan can remain adequate under many plausible climate futures, but only if the critical transmission corridors are reinforced in time and the four backbone connections identified in the robust policies are implemented.

5

Discussion and Future Research

This chapter reflects on the boundaries and shortcomings of the research and identifies directions for future work. Section 5.1 first summarises the main findings and then discusses the practical impacts and scientific implications of this study on the planning of power systems in Indonesia. Section 5.2 discusses the key limitations and assumptions of the study and suggests avenues for future research that could extend the findings to a more complete treatment of the Indonesian power system planning challenge.

5.1. Main Insights for Practice

This thesis examines Indonesia's long-term power system planning by evaluating planned infrastructure under deep climate uncertainty. It combined an energy system model with an exploratory modelling approach applied to Indonesia's supergrid plans to go beyond asking whether the planned system works in a baseline case and to identify the future conditions under which it remains adequate, where it becomes vulnerable, and which infrastructure choices most affect robustness. Under standard optimisation, the planned infrastructure appears sufficient to support a reliable and affordable energy transition. When stress-tested under deep climate uncertainty, the system remains within reliability thresholds by 2034, even under the harshest climate impacts. However, by 2045, under moderate to high combined climate stress, the system begins to fail, although policies designed for 2060 still hold. By 2060, even the maximum-capacity policy cannot withstand moderate combined climate stress. A pivotal intervention emerges by 2060. Reinforcing the Bali–Jawa Timur line keeps the grid robust in much more of the uncertainty space, and this reinforcement, together with the final identified HVDC backbone, matches the performance of the maximum-capacity policy while requiring far less investment.

5.1.1. Practical Contribution

This thesis offers concrete insights for long-term power infrastructure planning policy in Indonesia. The modelling shows that a supergrid is a logical and necessary response to Indonesia's geography and decarbonisation challenge. The main renewable resources are outside the main demand centre in Jawa-Bali, so inter-island transmission can move power from renewable-rich areas to load centres and support a long-term shift to a low-carbon system.

However, the supergrid also creates new dependencies. As Jawa–Bali relies more on imports, system adequacy hinges on a few inter□island corridors. Reliability is no longer just about having sufficient generation capacity, but also about whether key transmission corridors are strong enough and available under stress. The supergrid adds flexibility but also introduces critical links whose failure or under-dimensioning can severely undermine system adequacy.

This matters because the climate drivers studied here affect both sides of the adequacy problem. Higher temperatures can increase demand, while derating reduces available generation capacity. Other climate hazards such as flooding, storms, sea-level rise, and coastal exposure of landing stations may also threaten the physical availability of transmission assets. Policy-makers must seriously consider these risks. The supergrid can enable the energy transition in Indonesia, but it also creates a few crucial failure points. Climate-related disruptions to key lines could rapidly cut power to entire regions, and without sufficient backup generation or storage, those areas would lose electricity with no quick way to restore it.

The results show that the reliability threshold used by Indonesian system planners is crucial. At present, adequacy is judged against 24 lost-load hours per year. Given Indonesia's ambition for a highly reliable grid and a current SAIDI of 8.2, this thesis instead applies the stricter Western benchmark of 8 lost-load hours per year. Under the 24-hour criterion, the supergrid appears far more robust to the climate impacts studied. In this thesis's view, relying on this looser standard risks a false sense of security, masking emerging adequacy issues and delaying needed reinforcements to avoid unacceptable lost-load hours.

Another main finding is that robustness does not simply rise by maximising all supergrid capacities. Targeted reinforcement of critical corridors can be more effective than broad over-investment. The most important example is the Jawa Timur–Bali connection. In the original 2060 stress test, this fixed link becomes a binding constraint under combined demand growth and derating. Reinforcing it substantially improves robustness across scenarios. Indonesia should therefore focus not only on total inter-island capacity, but also on the location and timing of specific reinforcements. Priority should go to identified backbone lines, ensuring their capacity is delivered as early as possible and that sufficient budget is reserved. Because these lines are slow and costly to build, failing to prepare in time can allow problems to emerge before capacity is available.

The main policy implication is that robustness should become a central planning criterion alongside cost, emissions, and baseline adequacy. For Indonesia, the supergrid must be evaluated not only as a cost-optimal way to link renewable supply and demand, but also as critical infrastructure that must remain adequate in many climate futures. This requires early identification of critical corridors, stress-testing their adequacy, and reinforcing or building them before they become binding constraints.

A final practical contribution is the modelling workflow developed in this thesis. By linking the Calliope energy system model with the EMA Workbench and running the experiments on the DelftBlue high-performance computing cluster, the research creates a workflow for testing Indonesian power system plans in many uncertain futures. This workflow can be used as a basis for further research on climate-resilient net-zero electricity planning in Indonesia by researchers, policy makers, and engineers working on Indonesia's power planning. It also shows how exploratory modelling can support planning practice by turning uncertainty from something that is ignored or treated as a sensitivity into a central part of infrastructure assessment.

Taken together, these findings suggest that Indonesia's long-term electricity plans can remain adequate under many plausible climate futures, but not automatically. Adequacy depends on whether the right corridors are identified, reinforced, and built in time. The broader implication is that long-term power system planning under climate change should move from asking what the optimal plan is to asking which plans remain adequate in many plausible futures.

5.1.2. Scientific Contribution

This thesis treats the impacts of climate change on the adequacy of the power system as a source of *deep uncertainty* in long-term planning of the power infrastructure (Lempert et al., 2003; Marchau et al., 2019). It responds to calls to move beyond single-trajectory climate inputs and design for a wide range of plausible climate futures (Bloomfield et al., 2021; Santos et al., 2016), and builds on the relevant literature on climate-impact modelling and system-planning studies showing that higher temperatures can increase demand while derating capacity, with major implications for adequacy and costs (Aji et al., 2026; Craig et al., 2020; Sherman et al., 2022; Wang et al., 2025).

In the Indonesian energy-transition literature, the thesis complements decarbonisation pathway studies that emphasise inter-island transmission and high renewables but typically use cost-optimal single-route optimisation and do not stress-test plans against climate uncertainty (Aji et al., 2025; Handayani et al., 2022; Langer et al., 2024). Whereas these studies focus on what an efficient transition could look like, this thesis examines under which climate-stressed futures Indonesia's planned interconnections remain adequate, where they become vulnerable, and which links are most critical for robustness.

Methodologically, the thesis bridges two rarely connected fields: (i) climate-impact studies that include some climate effects but usually explore a narrow uncertainty space or a single climate trajectory (Haddad et al., 2025; Rosende et al., 2019), and (ii) DMDU applications that show the value of RDM for energy planning but often omit climate change from the uncertainty space or focus on generation rather than transmission adequacy (Paredes-Vergara et al., 2025; Sundar et al., 2024). By coupling a national-scale energy system model with an exploratory modelling workflow and applying it to Indonesia's supergrid plans, the thesis delivers an infrastructure-focused RDM stress test for Indonesia.

The results show that a plan performing well under baseline optimisation can still be fragile under other plausible futures. In baseline Calliope runs, the 2034, 2045 and 2060 systems show no lost-load hours, indicating adequacy in the expected case. Yet with higher demand and derated generation and transmission capacity, the same system can become inadequate. This supports the DMDU argument that long-lived infrastructure should be judged not only by optimisation but by stress testing across many plausible futures, especially when decisions lock in dependence on critical inter-island corridors.

5.2. Assumptions, Limitations and Future Research

Several modelling choices, research design choices, and major assumptions restrict how the results should be interpreted. These also point to several directions for future research.

The first major limitation of this research is its level of technical detail. This thesis assesses Indonesia's supergrid from a long-term planning and adequacy perspective, not an electrical-engineering one. The model tests whether demand can be met under different combinations of climate stress and infrastructure choices, but does not perform detailed power-flow calculations, voltage or frequency stability analysis, contingency analysis, or dynamic assessment of AC and HVDC operation. The findings therefore should not be read as proof that the proposed supergrid configurations are technically feasible under all operating conditions.

This matters because the transmission capacity is simplified. A line may seem sufficient because its modelled flow remains below its assumed capacity, while a more detailed grid model could reveal operational constraints, stability issues, congestion, or reactive power limitations that could change the assessed performance of specific interconnections. However, this choice is consistent with the purpose of the thesis. The goal is not to validate the detailed operation of the Indonesian supergrid, but to stress-test long-term infrastructure plans under deep climate uncertainty. Lost-load hours and reserve margins provide a solid first indication of whether planned infrastructure remains adequate in many plausible futures. The main contribution is to show how an uncertainty-aware planning approach can reveal vulnerabilities that a single baseline optimisation would miss. Future work should pair this exploratory modelling with detailed power-flow, stability, and contingency analysis to test whether the robust strategies identified here remain technically feasible at the operational grid level.

Furthermore, the uncertainty space in this study is shaped by specific scoping choices. Including additional uncertainties, such as accidents, cyberattacks, or sabotage,in future work could reveal new system vulnerabilities. Considering further factors, including those treated as constant here, could change the results and alter which uncertainties most affect the metrics examined. For example, future studies could incorporate the uncertainty of fuel prices. At the time of writing, the conflict in the Middle East and the blockade of the Strait of Hormuz are causing energy shortages and price spikes in Asia (Jaspal & Sagahyroon, 2026). Although this thesis assumes constant fuel prices, Indonesia is already shifting from gas to coal in response, affecting levelised consumer costs and emissions and potentially accelerating the transition to renewables, which in turn may require additional interconnection capacity sooner than expected. Uncertain technology costs could also raise or lower levelised costs and make alternative generation mixes more attractive. Uncertainty in policy timing and in the political feasibility of specific interconnections could also alter outcomes. Future research could therefore explore scenarios in which certain lines are never built, are constructed much later than planned, or face significant delays.

In addition, climate change uncertainties were simplified for computational feasibility, particularly for derating assumptions in exploratory analysis. The province-level technology-specific derating estimates under RCP 8.5 from Aji et al. (2026) were aggregated into four national levels: none, minimum, median, and maximum. The minimum, median, and maximum correspond to the lowest, middle, and highest derating percentages observed in the provinces for each technology. This simplification removed spatial variation in climate impacts. The results may therefore understate adequacy problems in provinces where local derating exceeds the national value, implying less available capacity and more lost load hours than reported, and overstate problems where local derating is lower. Future work should incorporate province-specific derating directly into the exploratory analysis to better capture local climate vulnerabilities and regional adequacy.

Including additional climate-change uncertainties could also substantially change the results. A key assumption was that capacity factors for several technologies remain constant. The capacity factors for wind, solar photovoltaic, and hydropower from Langer et al. (2024) were fixed until 2060, although future wind yields may change under climate change (Pryor & Barthelmie, 2010). Wind is a central part of Indonesia's strategy and is expected to exceed 11 GW by 2060 (MEMR, 2025a). It was also not derated in the exploratory analysis (see Table A.5 in the Appendix). Therefore, future work should test how lower wind yields would affect lost load hours, affordability (given the near-zero marginal costs of the wind) and emissions if more dispatchable generation is needed. Similarly, changing rainfall and run-off could alter hydropower inflows, increasing drought-related shortfalls and high-flow spill events. Empirical evidence already shows that climate variability can affect the availability of hydroelectric power and the adequacy of the power system (Haddad et al., 2025). Current policy documents propose a very large hydroelectric expansion in Kalimantan and associated HVDC links to Jawa and Sulawesi (MEMR, 2025a). Accounting for climate-driven hydropower uncertainty could shift the balance between renewables and dispatchable capacity and change which HVDC reinforcements are needed the most for a climate-robust grid. Finally, the network representation is simplified. The AC transmission capacity is assumed to be fixed, and the stress test does not model line outages or physical damage to HVDC cables and landing stations. Future work could explicitly model outages of HVDC corridors and landing stations to assess the impacts of flooding, storms, and sea-level rise.

The Calliope models simulated only selected critical periods, not a full year, so the results cannot guarantee the adequacy in every hour. This choice allowed the exploratory analysis to be completed within the thesis' time limits. Future work should extend the study to full-year chronological adequacy assessments for multiple years up to 2060 to test system performance under all conditions, not just stress periods. For instance, how would it perform during extended periods of low wind together with weak solar generation in the dry season?

A key assumption in this thesis was that only the 2024 load profiles for Jawa–Bali and Sumatra were available, so it was assumed that the other major islands share the profile of Sumatra. In reality, this may be inaccurate, so future work should use actual load profiles for each island. Using identical profiles synchronised the loads and amplified peak demand, which drives system collapse and violations of allowable lost-load hours. If real profiles are not perfectly aligned, combined peaks may be lower, meaning that the study may exaggerate the problem and overestimate the interconnection capacity needed for climate robustness.

Future research could expand the range of policy options. This study focuses on HVDC expansion as the main infrastructure lever through 2060 and holds other elements constant, but additional measures could improve system robustness. Future work could include AC grid reinforcements, storage capacity beyond current targets, vehicle-to-grid services for peak shaving, and demand-side flexibility. This would clarify which combinations of infrastructure and flexibility are most effective under deep climate uncertainty. Because most lost load hours occur in the Jawa–Bali system, adding another policy intervention there could lower the required interconnection capacity to meet the same reliability threshold without changing emissions or costs.

Lastly, future research should examine the societal impacts of supergrid expansion and Indonesia's path to net-zero emissions through the lens of energy justice as defined by Jenkins et al. (2016). Because interconnection projects require large investments, it is crucial to determine who bears the costs and who receives the benefits. From a distributional justice perspective, this means analysing which groups shoulder the financial burden, how investments affect electricity prices, and how the location of new hydrogen or ammonia facilities impacts nearby communities. From a procedural justice perspective, research should assess whether affected stakeholders are genuinely included in decision-making. This is especially important in Indonesia, where Indigenous communities depend on local ecosystems and must be involved in these processes (Fisher et al., 2018).

6 Conclusion and recommendations

6.1. Answer to main research question

This thesis investigated how deeply uncertain climate change impacts affect Indonesia's long-term power infrastructure plan. The main research question was:

What is the impact of deeply uncertain effects of climate change on the long-term power infrastructure plans of Indonesia?

The results indicate that Indonesia's planned supergrid can enable decarbonisation but simultaneously reconfigures where system vulnerabilities lie. As renewable generation shifts toward resource-rich regions, notably Kalimantan and the Nusa Tenggara islands, while demand remains concentrated in Jawa–Bali, adequacy becomes increasingly dependent on a small number of inter-island transmission corridors.

Deep climate uncertainty affects the plan in two connected ways. First, higher temperatures increase electricity demand while simultaneously reducing the available generation and transmission capacity through derating, shrinking the system's adequacy margin. Second, the planned infrastructure increasingly depends on the moving of electricity across islands to supply Jawa–Bali. Under climate stress, problems, therefore, do not appear evenly throughout the system but concentrate around specific transmission corridors. The plan can remain robust, but only if the most critical links are identified, sufficiently dimensioned, and built in time.

Sub-question 1: performance of the baseline plan. *How does the current long-term power infrastructure plan of Indonesia until 2060 perform against the key metrics of the number of hours with lost load, levelised system costs, total emissions, and regional reserve margin?*

Under the assumptions in the policy documents, the Calliope optimisation does not produce lost-load hours in the modelled periods for 2034, 2045, and 2060 (Table 4.1), while the emission intensity declines strongly towards 2060. System costs rise slightly, driven mainly by the shift to green hydrogen and ammonia co-firing, but remain relatively stable. However, regional reserve margins in Jawa–Bali and Sumatra deteriorate substantially by 2045 and 2060 (Tables 4.3 and 4.4). By 2060, the Jawa–Bali margin turns deeply negative, reflecting a structural dependence on electricity imports from the islands with the largest renewable potential. This also increases the importance of maintaining sufficient dispatchable generation capacity outside the main demand centre to serve as a buffer when transmission corridors are under stress.

Sub-question 2: robustness under climate uncertainty. *What impact do the deeply uncertain effects of climate change have on the robustness of different infrastructure development plans?*

The exploratory analysis shows that robustness is high in 2034. Even under the most severe combinations of demand growth and derating tested, all policies remain within the lost-load threshold. By 2045, vulnerabilities begin to emerge. Policies that keep the Bali–Nusa Tenggara Barat interconnector at its minimum capacity of 1000 MW fail under moderate to high climate stress, while policies that raise this connection to at least the intermediate level remain adequate across a much larger share of scenarios. By 2060, the two climate uncertainties, demand increase and derating, become the dominant determinants of system adequacy, outweighing the choice of supergrid configuration. No single policy remains robust against even a moderate combination of the two stressors. A targeted set of backbone connections matches the performance of the maximum-capacity configuration at considerably lower cost. Diagnostics identify the Bali–Jawa Timur connection, fixed at 2100 MW in the 10-year Electricity Business Plan, as a binding bottleneck under these conditions. Reinforcing this link to 7500 MW substantially restores robustness across most of the scenario space tested.

6.2. Recommendations

The findings of this thesis lead to four concrete recommendations for PT PLN and the Ministry of Energy and Mineral Resources.

Prioritise and build the supergrid backbone. The exploratory analysis consistently identifies four inter-island connections as the most critical for system adequacy under climate stress: the Jawa Tengah–Kalimantan Selatan link (26 GW), the Kalimantan Selatan–Kalimantan Utara link (15 GW), the Nusa Tenggara Timur–Sulawesi Selatan link (4 GW), and the Bali–Nusa Tenggara Barat link (at least 7.5 GW). These four corridors form the backbone of a climate-robust supergrid and should be treated as priority investments. Their construction should be started as early as possible, given the long lead times and high capital costs involved.

Reinforce the Bali–Jawa Timur connection beyond the current plan. The capacity of 2100 MW fixed in the 10-year Electricity Business Plan is insufficient under combined demand growth and derating by 2060. The analysis shows that increasing this connection to 7500 MW substantially improves robustness at the system level. PT PLN should assess whether this reinforcement can be incorporated into the current planning horizon or whether it requires a revision of the 10-Year Electricity Business Plan.

Examine different planning timelines for the years 2045 and 2060. By 2045, PLN faces a choice. Implementing only the 2045-optimised strategies provides robustness under moderate climate stress, but full robustness under the range of scenarios tested requires building toward the 2060 backbone capacities already by 2045. Given the long lead times for the HVDC infrastructure, PT PLN should assess whether early construction of the 2060-level infrastructure is feasible and cost-effective.

Adopt robustness as a formal planning criterion. The current planning approach optimises primarily for cost and emissions in a single baseline scenario. The results show that a plan that performs well in this baseline can still be fragile under plausible climate futures. PT PLN and MEMR should complement baseline optimisation with systematic stress testing in a range of climate-driven demand and derating scenarios, using lost-load hours as the primary adequacy metric. Adopting the stricter 8-hour reliability benchmark, in line with current SAIDI performance and with Western European planning practice, rather than the existing 24-hour Loss of Load expectation criterion, would provide a more robust basis for long-term investment decisions.

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A

Appendix

A.1. Load Duration Curves

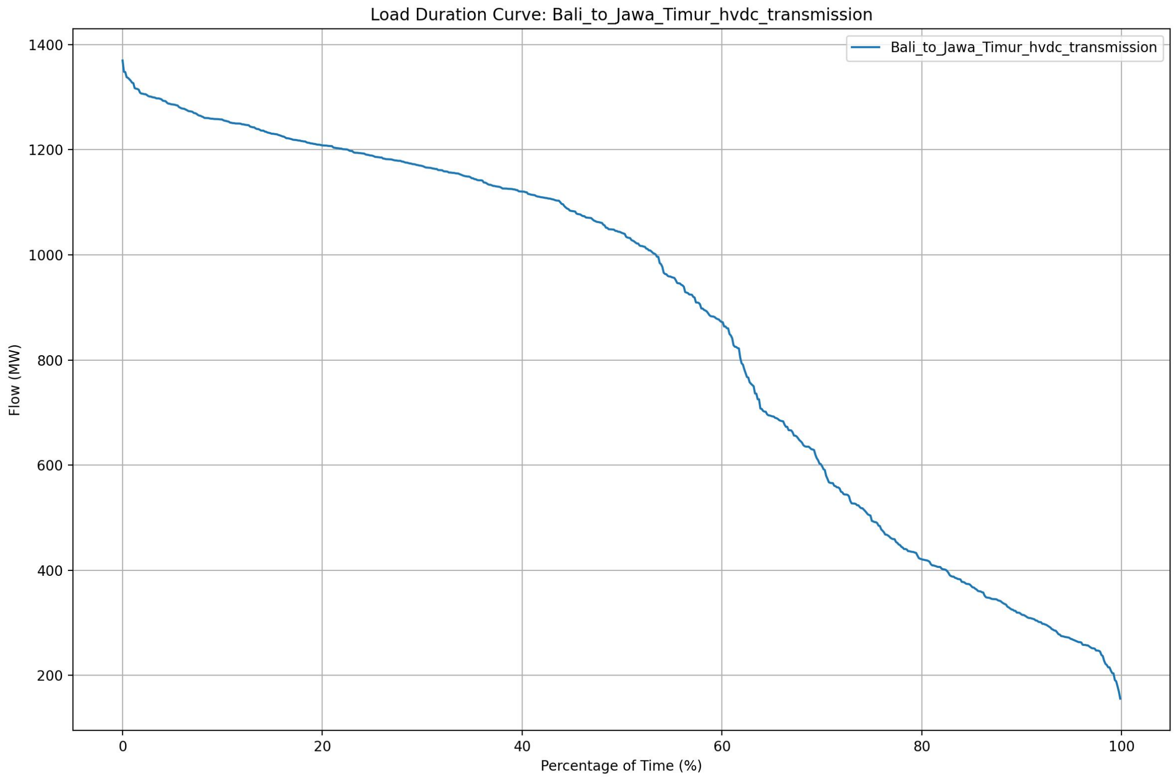

Figure A.1: Jawa–Bali supergrid load duration curve

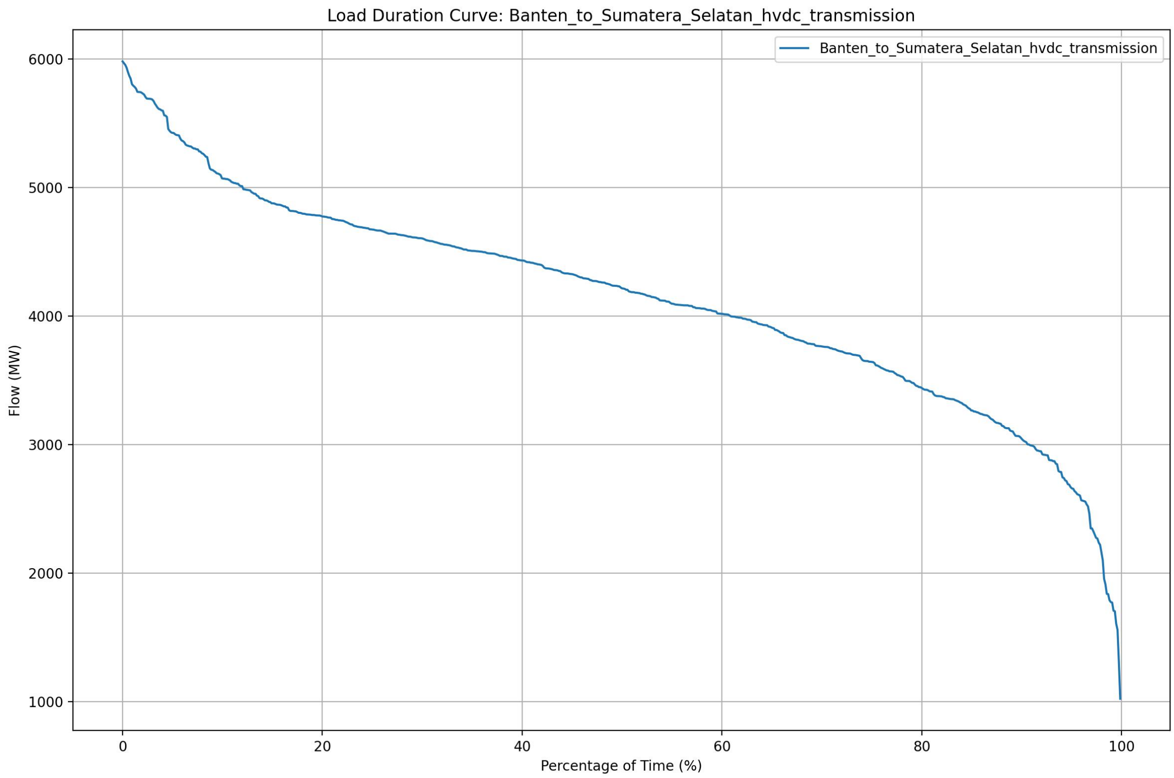

Figure A.2: Sumatra to Jawa supergrid load duration curve

A.2. Literature Review Article Overview

Table A.1: Overview of articles included in the literature review

Article	Year	Title
Aji et al. (2025)	2025	Considering Adaptive Power System Planning for Indonesia in the Face of Climate Uncertainties
Langer et al. (2024)	2024	The role of inter-island transmission in full decarbonisation scenarios for Indonesia's power sector
Handayani et al. (2022)	2022	Moving beyond the NDCs: ASEAN pathways to a net-zero emissions power sector in 2050
Haddad et al. (2025)	2025	Recent climate impacts on run-of-river hydropower and electricity systems planning in Switzerland
Wang et al. (2025)	2025	Climate change intensifies low-carbon transition pressure in China's power system
Craig et al. (2020)	2020	Compounding climate change impacts during high stress periods for a high wind and solar power system in Texas
Sherman et al. (2022)	2022	Projected global demand for air conditioning associated with extreme heat and implications for electricity grids in poorer countries
Rosende et al. (2019)	2019	Effect of climate change on wind speed and its impact on optimal power system expansion planning: The case of Chile
Bloomfield et al. (2021)	2021	Quantifying the sensitivity of European power systems to energy scenarios and climate change projections
Santos et al. (2016)	2016	A methodology to incorporate risk and uncertainty in electricity power planning
Paredes-Vergara et al. (2025)	2025	A framework for integrating deep uncertainty in power systems planning: an application to the Chilean case
Sundar et al. (2024)	2024	Identifying Robust Decarbonization Pathways for the Western U.S. Electric Power System Under Deep Climate Uncertainty

A.3. Technology and Cost Assumptions

Table A.2: Technical assumptions for generation, storage, and transmission technologies

Technology	Parameter	Unit	Assumption	Reference
CCGT with CCS	Efficiency	[%]	51	All (MEMR et al., 2024)
	Lifetime	[years]	-	
	Minimum load	[%]	45	
	CO_2 emission reduction	[%]	90	
Coal (subcritical)	Efficiency	[%]	37	All (MEMR et al., 2024)
	Lifetime	[years]	30	
	Minimum load	[%]	40	
CCGT	Efficiency	[%]	61	All (MEMR et al., 2024)
	Lifetime	[years]	25	
	Minimum load	[%]	15	
Onshore wind with BESS	Efficiency	[%]	85.36	(Langer et al., 2024)
	Lifetime	[years]	30	(MEMR et al., 2024)
	Storage loss	[% per day]	0.96	(Langer et al., 2024)
	Ratio between storage and energy capacity	[-]	0.25	(Lombardi et al., 2020)
Waste power plant	Efficiency	[%]	31	All (MEMR et al., 2024)
	Lifetime	[years]	25	

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Technology	Parameter	Unit	Assumption	Reference
	Minimum load	[%]	20	
Coal with CCS	Efficiency	[%]	30	All (MEMR et al., 2024)
	Lifetime	[years]	30	
	Minimum load	[%]	30	
CCGT + 100% H_2 co-firing	Efficiency	[%]	60	All (MEMR et al., 2024)
	Lifetime	[years]	25	
	Minimum load	[%]	10	
Coal + 100% NH_3 co-firing	Efficiency	[%]	34	All (MEMR et al., 2024)
	Lifetime	[years]	30	
	Minimum load	[%]	40	
Solar PV (utility-scale)	Efficiency	[%]	X	See note
	Lifetime	[years]	35	(Langer et al., 2024)
Solar PV with BESS	Efficiency	[%]	X	See note
	Lifetime	[years]	35	(MEMR et al., 2024)
	Storage loss	[% per day]	0.96	(Lombardi et al., 2020)
	Ratio between storage and energy capacity	[-]	0.25	(Langer et al., 2024)
Diesel (reciprocating)	Efficiency	[%]	48	All (MEMR et al., 2024)
	Lifetime	[years]	25	
	Minimum load	[%]	6	
Gas engine	Efficiency	[%]	46	All (MEMR et al., 2024)
	Lifetime	[years]	25	
	Minimum load	[%]	6	
Small hydro (run-of-river)	Efficiency	[%]	95	All (MEMR et al., 2024)
	Lifetime	[years]	50	
Pumped hydro storage	Round-trip efficiency	[%]	80	(MEMR et al., 2024)
	Lifetime	[years]	60	(MEMR et al., 2024)
	Storage loss	[% per day]	0.96	(Lombardi et al., 2020)
	Ratio between storage and energy capacity	[-]	0.15	(Langer et al., 2024)
Nuclear	Efficiency	[%]	42	All (MEMR et al., 2024)
	Lifetime	[years]	60	
	Minimum load	[%]	25	
Onshore wind	Efficiency	[%]	85.36	(Langer et al., 2024)
	Lifetime	[years]	30	(MEMR et al., 2024)
Biogas	Efficiency	[%]	35	All (MEMR et al., 2024)
	Lifetime	[years]	25	
	Minimum load	[%]	15	
OCGT	Efficiency	[%]	40	All (MEMR et al., 2024)
	Lifetime	[years]	25	
	Minimum load	[%]	15	
Biomass	Efficiency	[%]	32	All (MEMR et al., 2024)
	Lifetime	[years]	25	
	Minimum load	[%]	30	
Geothermal	Efficiency	[%]	16	All (Langer et al., 2024)
	Lifetime	[years]	30	
Battery (Lithium-iron)	Round-trip efficiency	[%]	92	(MEMR et al., 2024)
	Lifetime	[years]	30	(MEMR et al., 2024)
	Storage loss	[% per day]	0.96	(Lombardi et al., 2020)

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Technology	Parameter	Unit	Assumption	Reference
	Ratio between storage and energy capacity	[-]	0.25	(Langer et al., 2024)
Large hydro (reservoir)	Efficiency	[%]	95	(MEMR et al., 2024)
	Lifetime	[years]	50	(MEMR et al., 2024)
	Storage loss	[% per day]	0	(Langer et al., 2024)
	Ratio between storage and energy capacity	[-]	0.15	(Langer et al., 2024)
Micro hydro (run-of-river)	Efficiency	[%]	80	All (MEMR et al., 2024)
	Lifetime	[years]	50	
Onshore power transmission (AC)	Efficiency	[%]	98	(Langer et al., 2024)
	Lifetime	[years]	40	(Langer et al., 2024)
Sub-sea power transmission (HVDC)	Efficiency	[% per 1000 km]	96.6	(Langer et al., 2024)
	Lifetime	[years]	40	(Langer et al., 2024)

Note. X refers to the power production profiles used by Langer et al., 2024 in their model. They already accounted for efficiency in their underlying references. The technical data from 2050 is used for all technologies.

Table A.3: Cost assumptions for generation, storage, and transmission technologies

Technology	Cost component	Unit	Year		
			2034	2045	2060
Onshore wind + BESS	CAPEX	US$/kW$_p$	1200	-	-
	Fixed OPEX	US$/kW$_p$/yr	36	-	-
Onshore wind	CAPEX	US$/kW$_p$	1200	1013	890
	Fixed OPEX	US$/kW$_p$/yr	36	31.5	28.5
Solar PV (utility scale)	CAPEX	US$/kW$_p$	670	528	480
	Fixed OPEX	US$/kW$_p$/yr	6.8	6.2	5.9
Solar PV + BESS	CAPEX	US$/kW$_p$	670	-	-
	Fixed OPEX	US$/kW$_p$/yr	6.8	-	-
Geothermal	CAPEX	US$/kW	4400	4070	3850
	Fixed OPEX	US$/kW/yr	110	101.75	96.25
	Variable OPEX	US$/MWh/yr	0.27	0.25	0.23
Hydropower (large)	CAPEX	US$/kW	2110	1998	1920
	Fixed OPEX	US$/kW/yr	41	38.75	37.25
	Variable OPEX	US$/MWh/yr	0.71	0.67	0.65
Hydropower (small)	CAPEX	US$/kW	2400	2273	2190
	Fixed OPEX	US$/kW/yr	45.8	43.33	41.68
	Variable OPEX	US$/MWh/yr	0.55	0.52	0.50
Hydropower (micro)	CAPEX	US$/kW	2590	2448	2350
	Fixed OPEX	US$/kW/yr	58	55	53
	Variable OPEX	US$/MWh/yr	0.55	0.52	0.50
Nuclear (PWR)	CAPEX	US$/kW	7900	7075	6530
	Fixed OPEX	US$/kW/yr	120	114.75	111.25
	Variable OPEX	US$/MWh/yr	2.30	2.23	2.18
	Fuel costs	US$/MWh$_{thermal}$	2.90	2.90	2.90
CCGT	CAPEX	US$/kW	1030	970	930
	Fixed OPEX	US$/kW/yr	26	25.4	25
	Variable OPEX	US$/MWh/yr	2.50	2.43	2.38
	Fuel costs	US$/MWh$_{thermal}$	23.33	23.33	23.33
CCGT + CCS	CAPEX	US$/kW	-	1828	1610
	Fixed OPEX	US$/kW/yr	-	40.9	34.7

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Technology	Cost component	Unit	Year		
			2034	2045	2060
	Variable OPEX	US$/MWh/yr	-	3.81	3.44
	Fuel costs	US$/MWh$_{thermal}$	-	23.33	23.33
CCGT + H_2 co-firing	CAPEX	US$/kW	-	1265	1240
	Fixed OPEX	US$/kW/yr	-	26.67	26.46
	Variable OPEX	US$/MWh/yr	-	2.55	2.52
	Fuel costs	US$/MWh$_{thermal}$	-	60	60
Gas engine	CAPEX	US$/kW	750	-	-
	Fixed OPEX	US$/kW/yr	9.12	-	-
	Variable OPEX	US$/MWh/yr	6.84	-	-
	Fuel costs	US$/MWh$_{thermal}$	23.33	-	-
Diesel	CAPEX	US$/kW	910	-	-
	Fixed OPEX	US$/kW/yr	9.12	-	-
	Variable OPEX	US$/MWh/yr	6.84	-	-
	Fuel costs	US$/MWh$_{thermal}$	38.7	-	-
Coal (subcritical)	CAPEX	US$/kW	1820	1775	-
	Fixed OPEX	US$/kW/yr	50	48.91	-
	Variable OPEX	US$/MWh/yr	1.45	1.41	-
	Fuel costs	US$/MWh$_{thermal}$	12.05	12.05	-
Coal + CCS	CAPEX	US$/kW	-	2943	2600
	Fixed OPEX	US$/kW/yr	-	77.15	68.45
	Variable OPEX	US$/MWh/yr	-	3.83	3.58
	Fuel costs	US$/MWh$_{thermal}$	-	12.05	12.05
Coal + NH_3 co-firing	CAPEX	US$/kW	-	1845	1815
	Fixed OPEX	US$/kW/yr	-	48.92	48.10
	Variable OPEX	US$/MWh/yr	-	1.44	1.42
	Fuel costs	US$/MWh$_{thermal}$	-	166.4	166.4
OCGT	CAPEX	US$/kW	1060	-	-
	Fixed OPEX	US$/kW/yr	25.7	-	-
	Variable OPEX	US$/MWh/yr	3.50	-	-
	Fuel costs	US$/MWh$_{thermal}$	23.33	-	-
Biomass	CAPEX	US$/kW	2070	1883	1760
	Fixed OPEX	US$/kW/yr	49.7	44.8	41.6
	Variable OPEX	US$/MWh/yr	3.13	2.82	2.62
	Fuel costs	US$/MWh$_{thermal}$	9	9	9
Waste power plant	CAPEX	US$/kW	5520	5085	4800
	Fixed OPEX	US$/kW/yr	238.29	213.40	196.82
	Variable OPEX	US$/MWh/yr	24.80	24.13	23.68
Biogas power	CAPEX	US$/kW	2080	1900	1780
	Fixed OPEX	US$/kW/yr	101.7	91.8	85.2
	Variable OPEX	US$/MWh/yr	0.12	0.105	0.09
	Fuel costs	US$/MWh$_{thermal}$	9	9	9
Battery storage (4h)	CAPEX	US$/MWh$_{stor}$	330000	255000	210000
	Fixed OPEX	US$/MWh$_{stor}$/yr	10500	8138	6500
	Variable OPEX	US$/MWh/yr	1.8	1.65	1.55
Pumped hydro storage	CAPEX	US$/kW$_{stor}$	1800	1800	1800
	Fixed OPEX	US$/kW$_{stor}$/yr	18.7	18.7	18.7
	Variable OPEX	US$/MWh/yr	0.94	0.94	0.94
Transmission line (AC)	Fixed CAPEX	US$/kW	522	522	522
	Variable OPEX	US$/MWh/yr	1.3	1.3	1.3
Transmission line (HVDC)	CAPEX	US$/kW	170.557	170.557	170.557
	CAPEX per distance	US$/MW/km	293	293	293
	Variable OPEX	% of CAPEX	1.7	1.7	1.7

For 2034, the costs of 2030 are used. For the costs of 2045, we use interpolation between 2030 and 2050. The costs for 2060 in Table A.3 are extrapolated per technology and per cost component based on the shape of the cost trajectory between 2023, 2030 and 2050 (MEMR et al., 2024). To do this, the average annual change is calculated for the periods 2023–2030 and 2030–2050. If the annual change remains approximately constant between these periods, a linear extrapolation is applied. If the annual decrease in the second period is smaller than in the first period, a diminishing extrapolation is applied, whereby the reduction in the annual decrease is continued towards 2060. If a diminishing trend is identified, the annual decrease observed in 2030–2050 is reduced by 50% for the period 2050–2060.

A.4. Uncertainties, Levers, and Directed Search

Table A.4: 2034 model uncertainties and levers with explanation

Uncertainties	**Range**	**Explanation**
Demand increase	0%–27%	Each province's hourly electricity demand increases based on a province-specific ratio calculated from the stressed demand data from Hariadi Aji, see Table A.6.
Derating	0–3	Derating reduces each technology's capacity by a predefined percentage, based on a discrete derating level from 0 to 3 (none, minimum, median, or maximum reduction). These levels are derived from technology-specific capacity reduction percentages in the climate-derating dataset from Hariadi Aji, which reports derating per technology and province, see Table A.5. To keep the EMA analysis tractable, we replaced province-specific uncertainties with national derating values per technology, using the lowest, median, and highest derating from that dataset.
Levers	**Range (MW)**	**Explanation**
Bali–Jawa Timur supergrid link	[400, 1050, 2100]	Range provided by Hariadi Aji.
Banten–Sumatra Selatan link	[0, 3000, 6000]	Range mentioned in MEMR (2025a). We also test what happens if the project is not built due to delays.

Table A.5: Technology-specific capacity derating assumptions used in the exploratory analysis of 2034, 2045 and 2060

Technology	**None**	**Min.**	**Median**	**Max.**
Coal power plant	0.00	1.85	2.74	3.37
Combined-cycle gas turbine	0.00	7.35	7.71	8.40
Open-cycle gas turbine	0.00	8.67	10.24	11.01
Gas engine	0.00	2.74	4.04	4.97
Diesel power plant	0.00	2.74	3.94	4.97
Utility-scale solar PV	0.00	2.18	3.16	3.97
Solar PV with battery storage	0.00	2.18	3.16	3.97
Biomass power plant	0.00	2.24	2.52	2.98
Biogas power plant	0.00	9.79	10.65	11.35
Waste-to-energy plant	0.00	2.71	3.13	3.87
Nuclear power plant	0.00	2.74	3.94	4.97

The derating assumptions represent reductions in available generation capacity. Four derating levels are used in the exploratory analysis: none, minimum, median, and maximum. Under each level, the available capacity of each technology is reduced by the corresponding percentage. This allows the model to test how climate-driven capacity reductions affect system adequacy across different infrastructure strategies.

Table A.6: Provincial peak demand stress ratios used in the exploratory analysis of 2034

Province	Peak demand stress ratio
Aceh	1.033
Bali	1.267
Banten	1.031
Bengkulu	0.996
Daerah Istimewa Yogyakarta	1.044
Daerah Khusus Ibukota Jakarta	1.019
Gorontalo	1.060
Jambi	1.067
Jawa Barat	1.050
Jawa Tengah	1.046
Jawa Timur	1.054
Kalimantan Barat	1.036
Kalimantan Selatan	1.062
Kalimantan Tengah	1.043
Kalimantan Timur	1.064
Kalimantan Utara	1.049
Bangka Belitung Islands	1.032
Lampung	1.025
Nusa Tenggara Barat	1.120
Nusa Tenggara Timur	1.097
Riau	1.021
Sulawesi Barat	1.077
Sulawesi Selatan	1.046
Sulawesi Tengah	1.067
Sulawesi Tenggara	1.054
Sulawesi Utara	1.071
Sumatra Barat	1.021
Sumatra Selatan	1.013
Sumatra Utara	1.032

Peak demand stress ratios represent province-specific multipliers used to adjust electricity demand under climate stress. Each ratio is calculated as the stress peak demand divided by the original peak demand. A value above 1 indicates that the demand increases under stressed climate conditions, while a value below 1 indicates a decrease. These ratios are applied to the corresponding province when performing the exploratory analysis.

Table A.7: 2045 and 2060 directed search model uncertainties, varied levers, and fixed inter-island transmission links.

Item	Range / value	Explanation
Uncertainties		
Demand increase	2%	Initial stress.
Derating	1	Initial stress.
Varied levers (MW)		
Jawa Tengah – Kalimantan Selatan link	[2000, 12000, 26000]	Range based on MEMR (2025a).
Kalimantan Selatan – Kalimantan Barat link	[1500, 3000, 4300]	Range based on MEMR (2025a).
Kalimantan Selatan – Kalimantan Utara link	[2000, 6500, 15000]	Range based on MEMR (2025a).
Bali – Nusa Tenggara Barat link	[1000, 7500, 15000]	Range based on MEMR (2025a).
Nusa Tenggara Barat – Nusa Tenggara Timur link	[1000, 7500, 15000]	Range based on MEMR (2025a).
Nusa Tenggara Timur – Sulawesi Selatan link	[2000, 3000, 4000]	Range based on MEMR (2025a).
Sulawesi Tengah – Kalimantan Timur link	[1000, 3000, 5000]	Range based on MEMR (2025a).
Fixed links (MW)		
Bali – Jawa Timur link	2100	Fixed value (PT PLN, 2025a).
Banten – Sumatra Selatan link	6000	Fixed value (PT PLN, 2025a).

Table A.8: Candidate strategies identified by the 2045 directed search, expressed as transmission capacities in MW. The fixed Bali–Jawa Timur and Banten–Sumatra Selatan links remain at 2100 MW and 6000 MW respectively in all strategies.

Transmission link	Cand. 1	Cand. 2	Cand. 3	Cand. 4
Jawa Tengah – Kalimantan Selatan	12000	12000	12000	12000
Kalimantan Selatan – Kalimantan Barat	3000	3000	3000	1500
Kalimantan Selatan – Kalimantan Utara	2000	6500	6500	6500
Bali – Nusa Tenggara Barat	7500	7500	7500	7500
Nusa Tenggara Barat – Nusa Tenggara Timur	1000	7500	1000	1000
Nusa Tenggara Timur – Sulawesi Selatan	2000	3000	3000	3000
Sulawesi Tengah – Kalimantan Timur	1000	1000	1000	1000

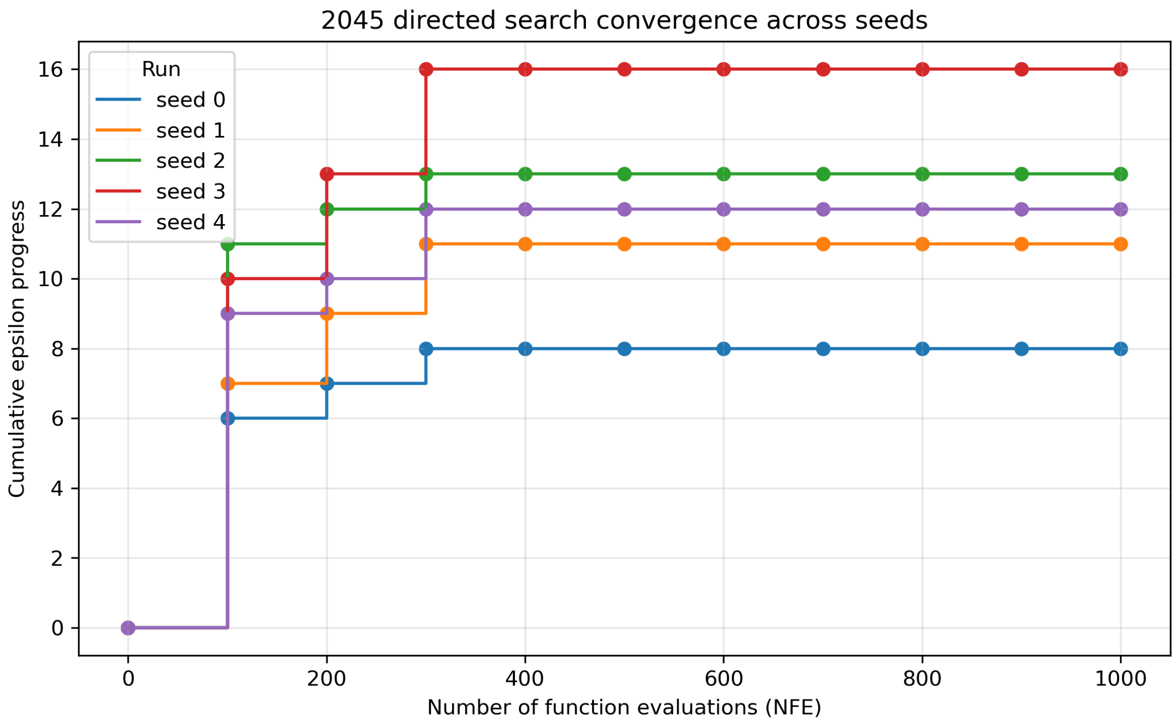

Figure A.3: 2045 directed search convergence across seeds

Table A.9: 2045 model uncertainties and levers with explanation

Uncertainties	**Range**	**Explanation**
Demand increase	0%–10%	Hourly electricity demand is scaled uniformly across provinces. The uncertainty is sampled using 30 Latin Hypercube samples.
Derating	0–3	Derating reduces available generation capacity. The four levels represent no, minimum, median, and maximum derating, see Table A.5.
Levers	**Range (MW)**	**Explanation**
Jawa Tengah to Kalimantan Selatan link	[2000, 12000, 26000]	Capacity options for the HVDC connection.
Kalimantan Selatan to Kalimantan Barat link	[1500, 3000, 4300]	–
Kalimantan Selatan to Kalimantan Utara link	[2000, 6500, 15000]	–
Bali to Nusa Tenggara Barat link	[1000, 7500, 15000]	–
Nusa Tenggara Barat to Nusa Tenggara Timur link	[1000, 7500, 15000]	–
Nusa Tenggara Timur to Sulawesi Selatan link	[2000, 3000, 4000]	–
Sulawesi Tengah to Kalimantan Timur link	[1000, 3000, 5000]	–
Fixed links	**Value (MW)**	**Explanation**
Bali–Jawa Timur link	2100	Fixed AC connection in the 2045 stress test.
Banten–Sumatra Selatan link	6000	Fixed HVDC connenction in the 2045 stress test.

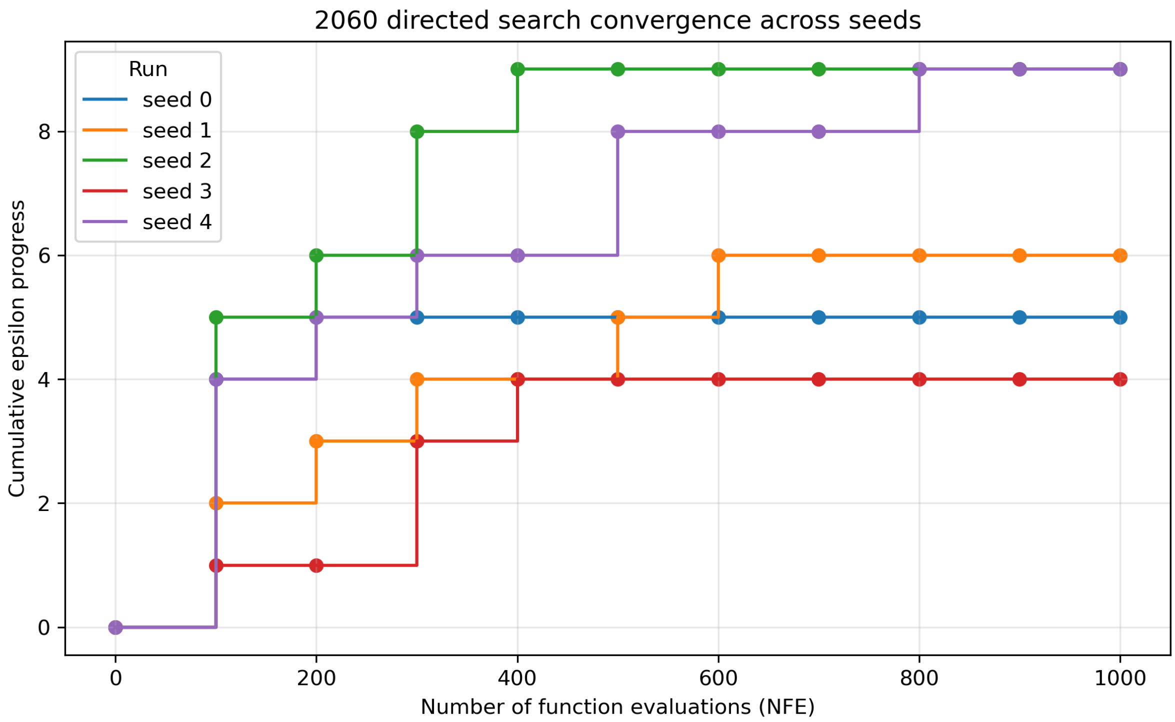

Figure A.4: 2060 directed search convergence across seeds

Table A.10: Candidate strategies identified by the 2060 directed search, expressed as transmission capacities in MW. The fixed Bali–Jawa Timur and Banten–Sumatra Selatan links remain at 2100 MW and 6000 MW respectively in all strategies.

Transmission link	Cand. 1	Cand. 2
Jawa Tengah – Kalimantan Selatan	26000	26000
Kalimantan Selatan – Kalimantan Barat	1500	4300
Kalimantan Selatan – Kalimantan Utara	15000	15000
Bali – Nusa Tenggara Barat	7500	7500
Nusa Tenggara Barat – Nusa Tenggara Timur	1000	1000
Nusa Tenggara Timur – Sulawesi Selatan	4000	4000
Sulawesi Tengah – Kalimantan Timur	3000	3000

Table A.11: 2060 model uncertainties and levers with explanation for the original and reinforced-link stress tests

Uncertainties	**Original 2060**	**Reinforced link**	**Explanation**
Demand increase	0%–5%	0%–10%	Hourly electricity demand is scaled uniformly across provinces. The uncertainty is sampled using 30 Latin Hypercube samples.
Derating	0–3	0–3	Derating reduces available generation capacity. The four levels represent no, minimum, median, and maximum derating, see Table A.5.
Levers	**Range (MW)**	**Range (MW)**	**Explanation**
Jawa Tengah to Kalimantan Selatan link	[2000, 12000, 26000]	[2000, 12000, 26000]	Capacity options for the HVDC connection.
Kalimantan Selatan to Kalimantan Barat link	[1500, 3000, 4300]	[1500, 3000, 4300]	–
Kalimantan Selatan to Kalimantan Utara link	[2000, 6500, 15000]	[2000, 6500, 15000]	–
Bali to Nusa Tenggara Barat link	[1000, 7500, 15000]	[1000, 7500, 15000]	–
Nusa Tenggara Barat to Nusa Tenggara Timur link	[1000, 7500, 15000]	[1000, 7500, 15000]	–
Nusa Tenggara Timur to Sulawesi Selatan link	[2000, 3000, 4000]	[2000, 3000, 4000]	–
Sulawesi Tengah to Kalimantan Timur link	[1000, 3000, 5000]	[1000, 3000, 5000]	–
Fixed links	**Original value (MW)**	**Reinforced value (MW)**	**Explanation**
Bali–Jawa Timur link	2100	7500	Fixed interconnection in both 2060 stress tests. In the reinforced-link version, this connection is increased to test whether the identified Jawa–Bali bottleneck can be relieved.
Banten–Sumatra Selatan link	6000	6000	Fixed HVDC connection in both 2060 stress tests.

The reinforced-link stress test differs from the original in two ways. First, the fixed capacity of the Bali–Jawa Timur connection is increased from 2100 MW to 7500 MW. Second, the demand increase range is widened from 0–5% to 0–10%.

A.5. AC Transmission Capacities

Table A.12: AC transmission capacity

Line	Capacity (MW)
Aceh – Sumatra Utara	5228
Bali – Jawa Timur	2100
Banten – DKI Jakarta	5200
Banten – Jawa Barat	7200
Bengkulu – Sumatra Barat	700
Bengkulu – Sumatra Selatan	2100
DIY Yogyakarta – Jawa Tengah	2400
Gorontalo – Sulawesi Utara	1400
DKI Jakarta – Jawa Barat	11 800
Jambi – Sumatra Barat	2156
Jambi – Sumatra Selatan	3156
Jawa Barat – Jawa Tengah	5600
Jawa Tengah – Jawa Timur	5100
Kalimantan Barat – Kalimantan Tengah	1400
Kalimantan Selatan – Kalimantan Tengah	2100
Kalimantan Selatan – Kalimantan Timur	2100
Kalimantan Tengah – Kalimantan Timur	700
Kalimantan Timur – Kalimantan Utara	2400
Kepulauan Bangka Belitung – Sumatra Selatan	1000
Lampung – Sumatra Selatan	5228
Riau – Jambi	1700
Riau – Sumatra Barat	2128
Riau – Sumatra Utara	2400
Sulawesi Barat – Sulawesi Selatan	1456
Sulawesi Barat – Sulawesi Tengah	1428
Sulawesi Selatan – Sulawesi Tengah	2184
Sulawesi Selatan – Sulawesi Tenggara	1428
Sulawesi Tengah – Gorontalo	1400
Sulawesi Tengah – Sulawesi Tenggara	728
Sumatra Utara – Sumatra Barat	1428

A.6. Reserve Margin Discount Values

The capacity credit assumptions in Table A.13 are used for variable technologies when calculating regional reserve margins. Firm technologies are counted at their full available capacity, whereas technologies listed in the table are discounted. For example, 100 MW of installed solar PV capacity contributes 22 MW to the reliable capacity used in the reserve margin calculation. Storage technologies, transmission technologies, demand, and lost load are excluded from the calculation of the reserve margin capacity, see Formula A.1.

Table A.13: Capacity credit assumptions used for reserve margin calculation

Technology	**Capacity credit**
Micro hydropower	0.55
Small hydropower	0.55
Large hydropower	0.55
Onshore wind	0.36
Wind with battery storage	0.36
Utility-scale solar PV	0.22
Solar PV with battery storage	0.22

$$RM_s = \frac{C_s^{\text{firm}} + C_s^{\text{credited}} - P_s^{\text{peak}}}{P_s^{\text{peak}}} \times 100 \tag{A.1}$$

Where C_s^{firm} is the total firm generation capacity in subsystem s, C_s^{credited} is the contribution based on capacity-credit of variable renewable technologies, and P_s^{peak} is the peak demand in subsystem s.

A.7. Typical Daily Demand Profile

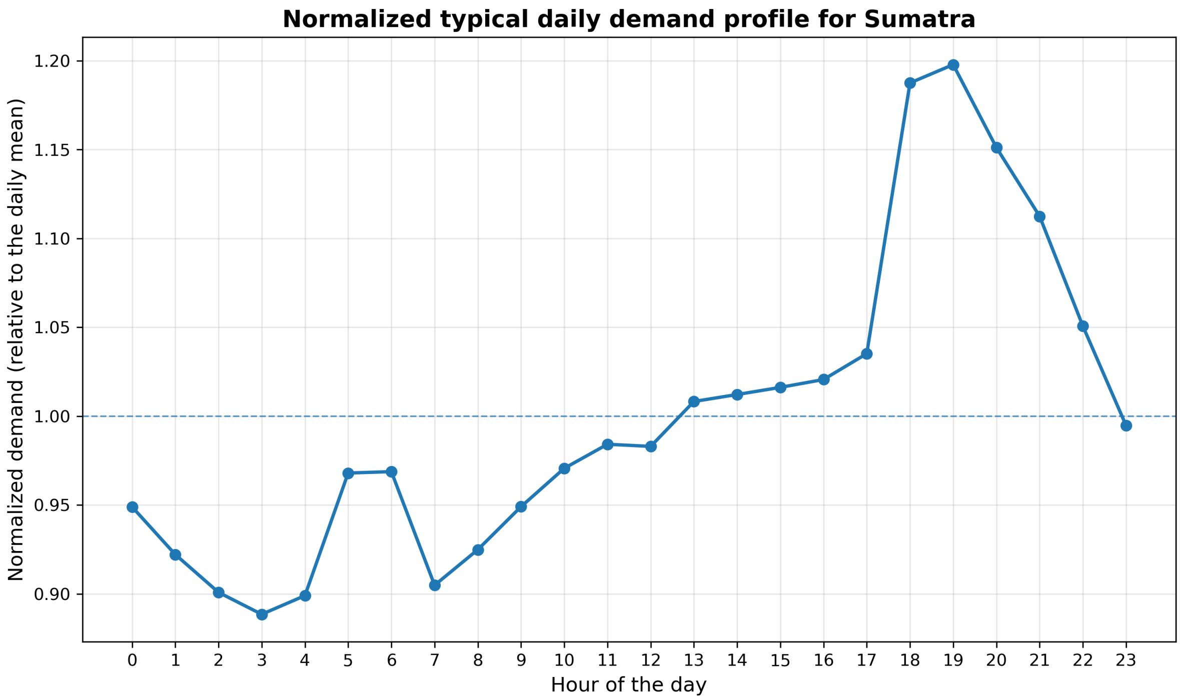

Figure A.5: Normalized typical daily demand profile for Sumatra.

A.8. Supergrid Lever Levels and Policy Definitions

Table A.14: HVDC lever capacity options used in the 2045 and 2060 stress tests. Lever levels 0, 1, and 2 select the corresponding capacity (in MW).

HVDC lever	Level 0 (MW)	Level 1 (MW)	Level 2 (MW)
Jawa Tengah–Kalimantan Selatan (jatengKalselHVDClevel)	2000	12000	26000
Kalimantan Selatan–Kalimantan Barat (kalselKalbarHVDClevel)	1500	3000	4300
Kalimantan Selatan–Kalimantan Utara (kalselKalutHVDClevel)	2000	6500	15000
Bali–Nusa Tenggara Barat (baliNtbAClevel)	1000	7500	15000
Nusa Tenggara Barat–Nusa Tenggara Timur (ntbNttHVDClevel)	1000	7500	15000
Nusa Tenggara Timur–Sulawesi Selatan (nttSulselHVDClevel)	2000	3000	4000
Sulawesi Tengah–Kalimantan Timur (sultengKaltimHVDClevel)	1000	3000	5000

Table A.15 shows the nine 2034 policies used in the exploratory analysis. The two varied levers are the Bali–Jawa Timur connection and the Banten–Sumatra Selatan connection. Each lever has three capacity levels, which results in all possible combinations of the two levers.

Table A.15: 2034 HVDC policy set.

Policy	BaliJatim capacity (MW)	BantenSumsel capacity (MW)
p1_bali0_sumsel0	400	0
p2_bali0_sumsel1	400	3000
p3_bali0_sumsel2	400	6000
p4_bali1_sumsel0	1050	0
p5_bali1_sumsel1	1050	3000
p6_bali1_sumsel2	1050	6000
p7_bali2_sumsel0	2100	0
p8_bali2_sumsel1	2100	3000
p9_bali2_sumsel2	2100	6000

Table A.16 shows the nine policies used in the 2045 stress test. Policy 1 represents the minimum-capacity configuration, Policies 2–5 are the four candidate strategies identified by the 2045 directed search, Policy 6 represents the maximum-capacity configuration, and Policies 7–9 are comparison policies derived from the 2060 analysis.

Table A.16: 2045 HVDC policy set. Entries indicate the selected lever level (0, 1, or 2) as defined in Table A.14.

Policy	jatengKalsel	kalselKalbar	kalselKalut	baliNtb	ntbNtt	nttSulsel	sultengKaltim
p01_all_zero	0	0	0	0	0	0	0
p02_ds2045_1101000	1	1	0	1	0	0	0
p03_ds2045_1111110	1	1	1	1	1	1	0
p04_ds2045_1111010	1	1	1	1	0	1	0
p05_ds2045_1011010	1	0	1	1	0	1	0
p06_all_two	2	2	2	2	2	2	2
p07_backbone_only	2	0	2	0	0	2	0
p08_ds2060_kalbar0	2	0	2	1	0	2	1
p09_ds2060_kalbar2	2	2	2	1	0	2	1

Table A.14 shows the thirteen policies used in both 2060 stress tests. Policy 1 represents the minimum-capacity configuration, Policy 2 the backbone only strategy, 3–10 are based on an L9-style design over the secondary levers, 11 and 12 are the two candidate strategies identified by the directed search and 13 represents the maximum-capacity option.

Table A.17: 2060 HVDC policy set. Entries indicate the selected HVDC lever level (0, 1, or 2) as defined in Table A.14.

Policy	jatengKalsel	kalselKalbar	kalselKalut	baliNtb	ntbNtt	nttSulsel	sultengKaltim
p01_all_zero	0	0	0	0	0	0	0
p02_backbone_only	2	0	2	0	0	2	0
p03_oa_A0B1C1D1	2	0	2	1	1	2	1
p04_oa_A0B2C2D2	2	0	2	2	2	2	2
p05_oa_A1B0C1D2	2	1	2	0	1	2	2
p06_oa_A1B1C2D0	2	1	2	1	2	2	0
p07_oa_A1B2C0D1	2	1	2	2	0	2	1
p08_oa_A2B0C2D1	2	2	2	0	2	2	1
p09_oa_A2B1C0D2	2	2	2	1	0	2	2
p10_oa_A2B2C1D0	2	2	2	2	1	2	0
p11_ds_candidate_kalbar0	2	0	2	1	0	2	1
p12_ds_candidate_kalbar2	2	2	2	1	0	2	1
p13_all_two	2	2	2	2	2	2	2