Exploring the Role of Long Duration Electricity Storage in Ensuring Adequacy

amid High Renewable Penetration and Future Climate Uncertainties

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by

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Abstract

In the context of increasing renewable energy integration and the push for decarbonization, this research addresses the need for long-duration electricity storage to ensure the reliability and adequacy of the future European power system. The variability of renewable energy sources such as wind and solar, coupled with the challenges posed by climate change, requires advanced storage solutions to balance periods of low energy generation and high demand.

This thesis explores how long-duration energy storage (LDES) and short-duration energy storage (SDES) can effectively contribute to resource adequacy by assessing various operational strategies, storage capacities, and system conditions. Using the Calliope energy system modeling framework, the research simulates a future interconnected European grid in 2050, considering different weather conditions and storage configurations to evaluate metrics such as Expected Energy Not Served and Loss of Load Expectation.

The results demonstrate that increasing the energy storage capacity and discharge duration of LDES significantly reduces LOLE, particularly during extended periods of low renewable output. However, SDES plays a complementary role, addressing short-term reliability challenges by reducing EENS during shorter disruption events. This combination highlights the need for a balanced deployment of both SDES and LDES to optimize grid performance and ensure resource adequacy. Through these findings, the thesis contributes valuable insights for energy planners and policymakers, aiming to foster a resilient, low-carbon electricity grid capable of meeting the demands of a renewable-dominated future.

Preface

I would like to use this space to thank all the people who collaborated in achieving my goals and in my academic and personal journey.

I would like to thank TU Delft and my thesis committee members. I am thankful to Dr. Kenneth Bruninx for sharing his perspective and expertise with great availability, which helped me improve this project. My deepest thanks go to my main supervisor, Dr. Simon Tindemans for guiding me in this process and helping me overcome the main difficulties of this project. I am also deeply grateful to my daily supervisor and company's buddy, Jaap Peterse and Eugenia Morino, who provided constant support and friendship. Finally, I would like to thank the entire Guidehouse Utrecht office for making their resources available to me and offering me the opportunity to get to know the world of consultancy more closely.

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Nomenclature

BPS	Bulk power system
CAES	Compressed air energy storage
CCS	Carbon capture and storage
COP282	United Nations Climate Change Conference
DE	TYNDP Distributed Energy scenario
DESSTinEE	Demand for Energy Services, Supply and Transmission in EuropE
DF	Dunkelflaute
E2P	Energy-to-Power
ECMWF	European Centre for Medium-Range Weather Forecasts
EENS	Expected Energy Not Served
EERA	European Resource Adequacy Assessment
ENTSO-E	European Network of Transmission System Operators for Electricity
FO	Forced Outage
FOR	Forced Outage Ratio
GA	TYNDP Global Ambition scenario
GCM	General Circulation Models
HDD	Heating Degree Days
LCOE	Levelized cost of electricity
LDES	Long Duration Electricity Storage
LOLE	Loss Of Load Expectation
LOLP	Loss Of Load Probability
MC	Monte Carlo
MSLP	Mean sea level pressure
MT	Medium-term
MTTF	Mean-time-to-failure
MTTR	Mean-time-to-repair
NFC	Number of Full Cycles
NT	TYNDP National Trend scenario
P2G	Power-to-Gas
P95	95th Percentile
PGP	Power-to-Gas-to-Power
PHES	Pumped hydro energy storage
RA	Resource Adequacy
RES	Renewable energy source
SDES	Short-duration Energy Storage
SOC	State-of-charge
TES	Thermal energy storage
TSO	Transmission System Operator
TTF	Time-to-failure
TTR	Time-to-repair
TYNDP	Ten-Year Network Development Plan
VOLL	Value Of Lost Load
VRES	Variable renewable energy sources
AUT	Austria
BEL	Belgium
DEU	Germany
DNK	Denmark
FRA	France
GBR	Great Britain
NLD	The Netherlands

1 Introduction

To keep global warming to no more than 1.5 °C as called in the Paris Agreement, the transition to net-zero emissions must be fully complete by 2050. On this matter, in December 2023 the United Nations Climate Change Conference (COP28) closed with an agreement that signals the “beginning of the end” of the fossil fuel era by laying the ground for a transition underpinned by deep emissions cuts and scaled-up finance [5]. Variable renewable energy sources(VRES) such as solar, wind, and hydropower will lead this transition and gain an increasing share in the power system, thanks to their economic competitiveness compared to fossil fuels. If on one side this represents a big achievement in the way of decarbonization, on the other side the intermittent nature of these sources due to climate dependency poses considerable challenges for energy planners and grid operators. Moreover, the electrification of different energy demand sectors (heating, industry, transport) will also result in an increased dependency of the electricity demand on weather conditions. For example, ENTSOe has identified for the winter of 2023 a small regional adequacy risk in and around France, with the highest probability of affecting Belgium and Great Britain in the event of an extreme cold spell, driven by the sensitivity of the demand in France to temperature and are present only under extreme weather conditions combined with high unplanned outages. [6].

Achieving reliable and affordable electricity systems may revolve around the capability of storing substantial amounts of low-cost energy over long durations. As renewable energy sources and short-duration electricity storage technologies (SDES) become more prevalent in the market, and as efforts towards deeper decarbonization intensify, long-duration electricity storage technologies (LDES) are gaining appeal to manage prolonged mismatches between energy supply and demand. These technologies can economically store energy for durations ranging from intra- to inter-day periods, bridging the gap between current short-duration batteries and seasonal storage The ability to provide energy during prolonged periods of low or no renewable generation allows LDES to support the three key goals of the energy transition: enhancing security, improving affordability, and reducing emissions from power supply [7].

LDES also has the potential to contribute to the resource adequacy of a power system, which is the ability to meet the energy demand at all times [8]. These technologies help balance the grid during peak demand periods, ensuring that the system has sufficient resources available. As power systems become more reliant on VRES, utilities will increasingly need to assess the role of LDES in maintaining resource adequacy and capacity value, the contribution a given generator makes to overall system reliability and adequacy [9].

Despite the promising potential of LDES, several challenges slow down its deployment. While pumped hydro energy storage (PHES) and compressed air energy storage (CAES) are commercially available at scale, advanced technologies like electrochemical storage are still in development, with limited demonstration at utility scale [10]. High initial costs, technological uncertainties, regulatory barriers, and the lack of established market mechanisms are among the primary obstacles that need to be addressed. For LDES to realize its full potential, it will require long-term vision and sustained investment from both public and private sectors, ensuring that it becomes a key element in a future electricity grid. Understanding the capacity value drivers of LDES is crucial for developing policies and strategies that can accelerate its deployment and integration into the energy system.

The above leads to the following research question:

What are the capacity value drivers of long-duration electricity storage for an interconnected European power system in 2050 in a context of high penetration of renewables and future climate?

The research question is broken down using the following sub-questions:

- *How is EENS affected by the operational profile of LDES?*
- *How is EENS affected by the discharge duration of LDES?*
- *How is EENS affected by LDES installed capacity and how does LDES interact with SDES?*

Report Outline

The report is structured as follows:

Chapter 2 presents the current state-of-the-art knowledge relevant to the topics addressed in this research, including resource adequacy assessments, the growing dependence of power grids on VRES and consequently the influence of meteorological conditions on resource adequacy shortfalls, and the need for flexibility solutions.

Chapter 3 introduces the main methods used by energy system modelers to reproduce the power system's random behavior and conduct system adequacy assessments through Monte Carlo simulations.

Chapter 4 explains how the methods previously introduced are used to build a European interconnected power system of the future and assess the contribution of LDES to the system's resource adequacy.

Chapter 5 analyses the simulation results.

Chapter 6 outlines and discusses the findings of this research and presents its limitations.

Chapter 7 presents the research conclusions, addressing the main research question.

2 Literature Review

This literature review aims to present the current state-of-the-art knowledge relevant to the topics addressed in this research. Section 2.1 explores frameworks used in resource adequacy assessments. Section 2.2 examines the impact of meteorological conditions on resource adequacy failures. Section 2.3 discusses various flexibility options that enhance grid reliability, with a particular emphasis on long-duration electricity storage solutions. Following these discussions, Section 2.5 identifies the existing knowledge gaps and outlines the research questions that this thesis aims to address.

2.1. Resource Adequacy Framework

One of the European Union's main objectives in energy policy is to provide secure, affordable and clean energy [11]. In agreement with this objective, energy planners and grid operators work to guarantee system security and adequacy. The concepts of system security and system adequacy are explained in Section 2.1.1, together with the main figures used to assess the adequacy of a system presented in Section 2.1.2. Finally, Section 2.1.3 presents a comparison between these metrics, while Section 2.1.4 shows the main downsides of traditional resource adequacy metrics.

2.1.1. General Introduction

"Security of Electricity Supply" stands as one of the fundamental aspects of the European Union's strategy for climate and energy [12]. Various aspects are considered in this matter, including system adequacy. Adequacy is defined as "a measure of the ability of a bulk power system to supply the aggregate electric power and energy requirements of the customers within component ratings and voltage limits, taking into account scheduled and unscheduled outages of system components and the operating constraints imposed by operations" [8]. While security deals with the operational aspects, adequacy is integral to the system's development and planning [12]. It involves the ability to meet long-term demand while considering supply-demand uncertainties and the extended time required for the capacity of network expansion.

Some of these uncertainties are gaining significance, such as correlated generator outages and weather variations [12]. Grid planners address these uncertainties by statistically evaluating them to project power grids' resource needs to reach an acceptably low level or risk of capacity shortages. Making an adequacy evaluation of the system can encompass these aspects [12]:

- Generation adequacy: assessing the capacity of the generation within a power system to meet its consumption requirements
- Transmission adequacy: evaluating the power system's ability to handle the power flow from generation to consumption centers.
- System adequacy: takes into account both generation and transmission adequacy.

Risk metrics can then be used to determine the necessary investments in power grids and the amount and type of generation to be constructed. The optimal adequacy should balance the investments needed to guarantee supply on every occasion and the cost of the energy not supplied to the customers [12].

European adequacy evaluations are conducted by the European Network of Transmission System Operators for Electricity (ENTSOe), the association for the cooperation of the 40 European Transmission System Operators (TSOs) who represent 35 countries and are responsible for the secure and coordinated operation of Europe's electricity system. This study aims to assess the generation adequacy of the European interconnected system, with a simplified approach to transmission modeling. Typically,

2.1.2. Adequacy Metrics

In evaluating generation adequacy, the underlying idea is that achieving absolute adequacy in an electrical system is practically unattainable without considering exorbitant investments. For this reason, in reality, the aim is to strike a balance between cost-effectiveness and reliability: system failure occurrences are tolerated when the resulting inconveniences for customers remain manageable or when there's a reluctance to invest more in enhancing reliability. Determining the acceptable level of unserved energy is typically done through reliability criteria. These metrics benchmark a system's readiness compared to a reference value called adequacy standards. By using adequacy indicators and comparing them to a reliability standard, it becomes possible to compare different systems and determine if a power system's level of adequacy is acceptable.

The European Commission describes the main adequacy indicators utilized in the European electricity market in [12]. This report aims to introduce the concept of adequacy and the main methodologies used in industry to assess the adequacy of a power system in Europe. The following sections present the main indicators of system adequacy with definitions found in this report.

Expected Energy Not Served (EENS) [GWh/year]

EENS represents the amount of electricity demand that is not met by the available generation plus imports [12]. Being a probabilistic metric [13], it can be obtained as an average of the Energy not Served (ENS) found across the simulations that are conducted [14], as described by the formula given by ENTSO-e in [15]:

$$EENS = \frac{1}{N}\sum_{j\in S} ENS_j \tag{2.1}$$

Where N is the number of simulations and ENS_j is the ENS of the j^{th} simulation [15].

Load Of Load Expectation (LOLE) [h/year]

LOLE measures the number of event periods, where an event period is a specified period (day, month, year) in which one or more shortfall events occur [16]. ENTSO-e defines LOLE as the average number of hours per year in which the available generation plus import cannot cover the load in an area or region [14]:

$$\mathrm{LOLE} = \frac{1}{N}\sum_{j\in S} LLD_j \tag{2.2}$$

where LLD_j is the loss of load duration associated with the j^{th} simulation and N is the number of simulations [15].

Loss Of Load Probability (LOLP)

The Loss Of Load Probability over a certain period represents the likelihood of experiencing at least one shortfall during that period, essentially indicating the probability of that being an event period. Although LOLE and LOLP are conceptually separate metrics, if the same period definition is applied to both, it is feasible to compute one metric in terms of the other.

95th Percentile (P95) [h/year]

The P95 values represent the 95th percentile, indicating the LOLE value that is near the maximum observed across all simulations, including the effects of weather and outages on the power supply. [17].

2.1.3. Comparison between metrics

Quantifying the EENS is the most straightforward method for monetizing interruption costs to compare possible investments aimed at achieving adequacy targets. In fact, according to [12] to assess the economic value of supply reliability or the financial impact resulting from interruptions, relevant cost metrics should be expressed as €/interruption, €/kW of peak load, €/kWh of annual energy consumption, or €/kWh of ENS.

While LOLE is commonly used due to its simplicity, it lacks information about the severity of the issue, as it is possible to get different LOLE while keeping the EENS constant [18]. For instance, a system-wide blackout or small demand reductions caused by the inability to meet peak demand can result in the same total number of hours of LOLE [12]. This can lead current metrics to overlook the considerably greater impact of these large events on consumers and society as a whole.

In [12], the European Commission outlines the key characteristics of each metric discussed, providing readers with guidance on when it may be appropriate to use each one.

Table 2.1: Comparison between resource adequacy metrics. Retrieved from [12]

Metric	Advantages	Disadvantages
EENS	• Quantification of ENS: possibility of monetizing interruption costs. • It accounts for the magnitude of shortages.	• A comparison between electricity systems of different dimensions is not possible but with a normalization of EENS.
LOLE	• Simple definition of the probability of encountering problems. • Widely used and accepted in the industry, facilitating benchmarking. • Focus on the frequency of outages.	• The magnitude of the issue is not measured, as it depends on how the electricity system is operated under critical conditions. • Lack of economic perspective.
LOLP	• Simple way to define the likelihood of coming across problems. • Option to compare electricity systems of varying sizes.	• The magnitude and duration of the issue are unquantified. • Lack of economic perspective.
P95	• It shows extreme values, helping in understanding worst-case scenarios • Useful for planning against high-impact, low-probability events	• If there are very extreme outliers in the simulation data, the P95 value can be significantly influenced by these ones, potentially skewing the perception of risk. • Focuses on extreme cases and might not represent typical performance, so it may lead to a disproportionate focus on high-risk scenarios.

2.1.4. Current challenges

Traditional resource adequacy metrics have been criticized in several ways [19]. First, the existing metrics focus on a single aspect of energy shortfalls, such as their frequency, duration, or magnitude. However, there is a growing recognition of the need to transition towards compound metrics or multiple metrics that offer a more comprehensive understanding of the adequacy challenges faced by the system. These broader metrics could better inform the types of resources required to address specific types of energy shortfalls. Secondly, while current metrics provide an average or aggregate characterization of shortfalls, they lack information on the distribution of frequencies, durations, or magnitudes of individual events. While using multiple metrics could address some limitations, there's still valuable insight into the distribution of shortfall events that are commonly not captured.

2.2. Meteorology and Resource Adequacy Failures

The upcoming energy transition will enhance the role of renewable energy sources in future power systems. Using intermittent sources will also increase the dependency of power grids on the weather. It is therefore important to consider the impact of meteorology on resource adequacy. While the main current situation and research trends in this matter are presented in respectively Section 2.2.1 and Section 2.2.2, Section 2.2.3 presents current challenges when taking into account climate variability in resource adequacy assessments.

2.2.1. General Introduction

Policies promoting low-carbon energy generation have significantly increased renewable energy production, displacing traditional thermal sources. According to [12], owing to their low operating costs, renewables now rank higher than flexible thermal plants in the merit order. Consequently, there has been a substantial decrease in the utilization of thermal plants, with their average utilization rate dropping from 50% to 37% between 2008 and 2013 [20]. This decline in flexible thermal generation, crucial for managing fluctuations of renewable energy production, poses challenges in ensuring grid adequacy in electricity markets.

While in traditional resource adequacy (RA) assessments resources are predominantly dispatchable, in the future resources will become predominantly non-dispatchable [19]. As a consequence, instead of focusing on probabilities of discrete independent mechanical or electrical failures, weather-influenced correlated events should now be recognized as a driving factor of reliability. In traditional resource adequacy analysis, periods with a higher likelihood of shortages were typically associated with peak loads, as variable resources constituted a small portion of the resource mix. However, the periods posing a risk of shortage are now shifting. For example, in the case of solar power, the diurnal pattern causes a decline in solar production at the end of the day. Additionally, extended cloud cover can further reduce solar output as storms pass through a region. Similarly, for wind generators, wind speeds can be correlated as different atmospheric conditions or storm fronts move through a region.

There is a growing discussion on the need for new flexible resources to support the variability of renewable generation [12]. Renewable energy sources can experience rapid and unpredictable changes. To meet demand at all times, these supply variations can be addressed through quick-responding generation, energy storage, or demand adjustments [12]. These elements underline the importance of considering weather when considering the resource adequacy of the power grid and the potential need for a source of flexibility.

2.2.2. Research trends

Reliability partly depends on maintaining resource adequacy, which pertains to the system's ability to consistently match electricity supply (or generation) and demand despite unforeseen circumstances. In this matter, meteorological conditions can contribute to disruptions by straining generation capacities, impairing transmission networks, and amplifying fluctuations in demand. RA failures, i.e., times where demand exceeds supply operationally at bulk power systems (BPS) level, are often responsible for large-scale rolling outages, e.g., in California in 2020 [21] and Texas in 2021 [22]. These two events were caused by a combination of higher than anticipated demand, due to respectively a heatwave and a cold snap, and generator outages driven by extreme weather. In Europe in 2003, due to a hot and dry summer, demand seriously threatened to exceed supply in several countries [23]. More recently, in 2022, hydro generation hit a record low due to extreme droughts, and nuclear generation dropped to the lowest output in 30 years due to unexpected outages at French nuclear plants [24].

All of these events required action, such as implementing rolling outages, by the system operator to avoid severe consequences for the system. Therefore, recognizing the primary meteorological factors contributing to power system strain is crucial for policymakers, grid operators, and energy stakeholders to enhance the future European power grid in the face of a growing reliance on VRES and climate unpredictability.

From the literature, three main fields of research are found at the intersection between meteorology and resource adequacy:

- The main meteorological drivers of European power system stress
- The increasing penetration of wind and solar power
- The non-static meteorology caused by natural variability and anthropogenic climate change

These trends and their research gap and challenges are investigated in the sections below. This investigation is particularly relevant to the research presented in this report because it directly addresses the critical issues of including meteorology in resource adequacy assessments.

Main meteorological drivers of European power system stress
Due to the variability of renewable, weather-dependent energy sources across different temporal scales, it is crucial to understand how meteorological conditions influence this variability and, consequently, power system stress. This understanding is essential for the efficient operation of a power system.
Peak demand is the highest amount of electric demand in a particular period. In contrast, net demand is the total electricity demand in the system minus utility-scale wind and solar generation. For this reason, daily peak net demand can occur at a different time than peak demand [25]. Most of the literature studies the meteorological conditions and weather patterns that lead to peak and net demand by correlating particular weather variables of a region to the electricity demand. Temperature is the variable that is mostly correlated to part of the demand [26], for example for heating and cooling. According to [27], since weather data typically have a longer and more consistent historical record than electricity demand data, working directly with weather data would be more advantageous to analyze its relationship with electricity demand instead of relying solely on observed demand data. This approach allows for a deeper exploration of how weather conditions influence demand patterns and system stress.

In countries with a winter demand peak, the availability of wind can be uncertain due to different meteorological conditions. Several studies have examined the potential for the availability of wind generation at peak demand, with the term ”low wind, cold snap” being used in the literature to describe times of potential concern for winter peaking energy systems [28]. Another extreme meteorological event is the so-called anticyclonic gloom described by the German term “Dunkelflaute” (DF). Generally, this event is characterized by the simultaneous occurrence of calm winds and dense cloud cover in winter. According to [29], an event is classified as DF if the solar and wind capacity factors are below 20% of the historical average for more than one day. Bloomfield [30] examines mean sea level pressure (MSLP), 100 m wind speed, 2 m temperature, and surface solar radiation anomaly composites during Europe’s ten highest peak load events to identify the typical meteorological conditions associated with such events. The study reveals that during peak demand periods, Europe tends to experience high-pressure systems, leading to abnormally cold temperatures in the region. High-pressure systems are areas in the atmosphere where air is sinking, leading to stable and dry weather conditions. Large negative near-surface wind speed anomalies were found in northern France, Belgium, the Netherlands, northern Germany, and the UK, and even larger negative anomalies offshore in the North Sea, resulting in below-average wind power generation throughout the UK, Netherlands, Belgium, and Germany.

In his analysis regarding GB’s weather, Dent [27] agrees with the result, confirming that the presence of this high-pressure system is observed consistently during severe weather events or periods of extreme conditions. High-pressure weather conditions usually present calm, clear, sunny conditions and consequently an above-average surface solar radiation [30], so one could think that the low wind power output could be compensated by solar power. However, Pfenninger [31], which presents the correlation between national wind and PV output for simulated future 2030 fleets in the UK, shows that the increased capacity of wind energy by 2030 contributes to heightened variability, imposing strain on the rest of the power system. Conversely, PV generation tends to lag during winter months, exacerbating the challenge of meeting increased energy demand during this time.

Another event associated with times of power system stress is the so-called ”heat wave”. In summer, maximum electricity demand for cooling is needed, but from the resources point of view, summer wind presents a minimum on its annual cycle, so a combination of maximum electricity demand can coincide with a minimum of wind power production. Molina et al. [32] shows that during heat wave events, an increase of 3.5%–10.6% in electricity demand and a decrease up to −30.8% in wind power production is obtained, with variability depending on the country. These results therefore add to the need for new flexibility options such as interconnection, storage, and load-shifting to help balance and harness this output.

The increasing penetration of intermittent generation

Wind and solar power generation are inherently variable and dependent on meteorological conditions such as wind speed, solar radiation, and cloud cover. Unlike conventional fossil fuel-based generation, which can be dispatched as needed, renewable energy generation is subject to weather patterns. Wind speeds and solar irradiance exhibit significant spatio-temporal variability and forecast errors [33]. As a result, the availability and output of wind and solar power can fluctuate widely over short time scales, leading to increased uncertainty in electricity supply and demand balance and a more complicated framework to do RA assessments. Since wind and solar power are a function of wind speeds and solar irradiance, increasing wind and solar power penetrations will increasingly link electricity supply and demand to these meteorological variables. For this reason, it becomes imperative to understand their variability and impact on the power system.

To keep pace with the increasing penetration of renewable power generation, energy modelers have been moving from using average annual or seasonal capacity factors to time series data [31]. In this way, it is possible to capture periods of power system stress, for example when both wind and solar power output are low. The first studies on this matter tended to use a single or typical year of generation data, however overlooking the substantial year-to-year fluctuation in weather or considering a single country in isolation, which ignores the possibility of balancing renewable intermittency through international connection [34]. Collins et al. [35] use a continental electricity system planning model and 30 years of hourly wind and solar data to determine the impact of long-term weather patterns on the operation of the European electricity system. The results show that the variability of CO_2 emissions and total generation costs for this system could increase 5-fold by using multiple years. Moreover, the study finds a strong correlation between VRES penetration and increased variability in the operation of conventional generators, primarily those that offer baseload power, playing a key role in balancing resource availability. However, storage technologies such as pumped hydro and battery storage capacity are not included in the study and the influence of weather on power demand is not considered.

For a case study in Britain, Staffell et al. [36] combines an analysis of weather-affected wind and solar generation and demand over multiple decades in an attempt to capture a fuller range of weather events. This helps to quantify the variability of the net demand that will have to be supplied by conventional generators. The study finds that the year-to-year variability of net electricity demand will increase by 80% by 2030 and that selecting a single year rather than 25 historical can result in a minimum net demand ±13% away from the 'true' mean. This underscores the importance of considering multiple years to achieve more reliable and representative results in analyzing electricity demand trends. On the other hand, Dent [27] suggests that historical weather records may be influenced by a few specific years, potentially skewing our understanding of past weather patterns. Longer records tend to reveal more extreme outlier events, such as harsh winters in the 1980s or specific years like 1962-1963 and 1946-1947. In summary, the literature underscores the need for careful interpretation and consideration of historical data in understanding past weather patterns and trends.

Non-static meteorology caused by natural variability and anthropogenic climate change

The system transformation of the energy sector needed to reach the European sustainability goals will increasingly couple energy supply and demand with weather and climate. Energy system modelers have succeded in representing the impact of present-day weather and climate to guarantee a reliable energy system that is resilient, affordable, and sustainable [37]. This means taking into account the variability and uncertainty of the present weather and climate. However, there is still a disconnect between the energy modeling community and climate modelers regarding what concerns the representation of the future climate [37].

Several studies in the literature have pointed out the different concerns that non-stationary meteorology imposed by anthropogenic climate change and long-term variability may impose on the energy system. A change in the meteorological and hydrological conditions could affect the whole energy chain. From the supply side, renewables will likely be affected by climate change. In particular hydropower and thermoelectric generation in Europe could decrease by up to 20% in a +3 ◦C global warming scenario according to [38]. Moreover, the temporal characteristics of wind power generation can be subject to climate change, leading to a higher probability for long periods of low wind power generation and a stronger seasonal wind variability [39] [40]. This greater variability could cause a higher frequency of energy droughts, mainly a sequence of days with energy production below a threshold or with a significant mismatch between VRES production and demand [41]. Moreover, extreme temperatures and weather events may cause big fluctuations in the hourly peak electricity demand of the system needed for heating and cooling [42] or infrastructural damage to the power grid [43].

As extreme weather driving these events (e.g., heat and drought) is projected to increase in severity and/or frequency under climate change [44], taking into account climate change becomes necessary not only for climate modelers but also for energy planners that want to guarantee the reliability and resilience of an energy system. European Resource Adequacy Assessment EERA 2023 takes into account climate change scenarios [45] in a simplified manner using a transitionary solution while an enhanced and forward-looking Pan-European Climate Database for future resource assessments is currently under development.

2.2.3. Current Challenges

As the energy transition entails a higher dependence of the electricity sector on meteorology, the availability and the use of high-quality meteorological data in energy system modeling becomes more and more important. Weather variables such as temperature, wind speed and solar irradiation are important to model the demand and renewable generation of a system. It is well documented the correlation between demand and temperature, with high temperatures resulting in increased demand for cooling and lower temperatures in increased demand for heating [26]. Solar and wind power generation can be modeled using solar radiation and wind speed data. Wind power relates to wind speed at wind turbine hub height and solar power generation predominantly relates to the amount of incoming solar radiation on the solar panel. However, climate model data are usually difficult to interpret and non-accessible to energy system planners, for example, due to the need for interpretation and calibration of a large volume of weather data. Bloomfield et al. [2] outlines the requirements of a dataset that can be properly used by planners in their analysis:

- They need hourly resolution: Power system planning models need to be run at a high temporal resolution such as hourly, to consider potential operational constraints and change in generation and demand patterns.
- They use a multi-decadal historical period to account for the impact of inter-annual variability
- They take climate change into account

Several weather variable datasets are available in the literature that satisfy the first two requirements, such as Copernicus Climate Data Store [46] and Renewables Ninja [47]. However, most of the datasets are based on historical observation and do not take into account future climate projections. Alternatively, datasets can be obtained through General Circulation Models (GCMs) which represent physical processes in the atmosphere, ocean, cryosphere and land surface. These models are the most advanced tools currently available for simulating the response of the global climate system to increasing greenhouse gas concentrations [48]. However, the use of climate models for present and future climate presents its challenges. First, while they include the impact of climate change on the weather, they do not have the temporal resolution required, as they are usually presented with a 3-hourly or daily resolution [38] [39] [40]. Second, there is the fact that climate models have their limitations and uncertainty. GCMs and climate models are probabilistic and can show a range of projections that could change depending on the particular model that is used. For example, for many regions projected change in rainfall varies from an increase in some GCMs to a decrease in others [49]. On this matter, Bloomfield et al. [50] underscores the importance of considering multiple climate models and projections, especially when addressing extreme generation scenarios like wind/solar droughts. The diverse responses in future climate projections emphasize the critical need for power system planners to avoid relying solely on multi-model mean climate projections (i.e., the average of multiple model simulations) and instead utilize these findings to establish a confidence interval of likely outcomes. Third, GCMs do not reproduce accurately some important drivers of weather in Europe related to the boundary of air masses that play a significant role in shaping regional weather patterns. In particular, they do not reproduce well storm tracks across Europe, at a latitude of 50-60° and areas of high pressure, which are important drivers of the power system stress as described in Section 2.2.2 [27].

As climate change does not imply the recurrence of cold spells again, there can be gaps in understanding the full spectrum of risks and potential outcomes associated with climate change. For these reasons, historical climate data and scenarios can provide valuable insights into potential future climate conditions and provide valuable and understandable insights to the community of electricity system planners and policymakers. These scenarios may need to be reweighted or adjusted to account for the likelihood of climate change impacts, similar to how the severe winter of 1962-1963 is considered in assessing future risks [27].

2.3. Energy Storage for Net-Zero and Resource Adequacy

The previous sections introduced the concept of resource adequacy and the future challenges energy planners will have to deal with to guarantee the security of supply due to the increasing dependency of power systems on climate variability. This part of the literature review introduces the role of energy storage as a potential solution to cope with this problem. First, an overview of different types of storage is presented in Section 2.3.1. Long-duration electricity storage and its potential contribution to resource adequacy are explained in Section 2.3.2, while the main technological options for this type of storage are shown in Section 2.3.3.

2.3.1. General Introduction

In the future, a significantly higher reliance on weather-dependent renewables can be expected, alongside expanded storage and greater interdependence with neighboring countries via electricity interconnection. Renewable generation output may drop substantially during certain weather conditions, such as periods of low wind or sunlight. These weather patterns could extend beyond individual countries, impacting neighboring nations as well. While consumers may shift their electricity usage away from such times, there may be limits on how much, or for how long, they can shift. Sufficient additional resources in the resource mix to deliver clean, reliable power at these times i.e. to maintain security of supply and ensure adequacy. Flexibility and resiliency measures are needed to address the fluctuations in supply and demand, which can occur at different timescales from minutes to hours to multiple days [51] as well as across years and decades [52], and ensure reliable and cost-effective power system operations. Flexibility measures can entail supply and reserve sharing, flexible generation, wind and solar generation ratio, demand response, curtailment and electricity storage. The consideration of multiple flexibility options has synergistic and complementary effects. According to [53], power system flexibility types and resources can be categorized at different timescales.

Energy storage can provide a series of services to power systems, including energy arbitrage; transmission and distribution congestion relief; investment deferral; demand shifting and peak reduction; spinning and non-spinning reserves; and seasonal energy shifting. Understanding the characteristics and applications of different energy storage is essential for designing resilient and sustainable energy systems at every timescale. Electricity storage technologies can be categorized based on their discharge duration time, which can vary from a few seconds to several weeks (Figure 2.1) [53]. The relationship between specific power and specific energy investment costs reveals whether storage technologies are more economically viable for short-duration or long-duration applications (Figure 2.2) [53]. Energy storage systems with lower energy investment costs are advantageous for storing large quantities of energy, making them suitable for long-term application. On the other hand, systems with lower power capacity costs encourage a high power demand and short-term usage.

Electrical storage is best suited for small energy capacities and short durations. On the other hand thermal, mechanical, and electrochemical storage technologies are appropriate for medium-sized energy capacities and can handle discharge durations ranging from short to long. Chemical storage is ideal for large energy capacities and long discharge durations because of the lower cost of storing chemical compounds.

Schmidt et al. [53] organizes the main energy storage technologies commercially available based on discharge duration. The technologies showed in Figure 2.1 are briefly presented below [53]:

- Short-duration storage (seconds to minutes):
  - Supercapacitors: Supercapacitors are ideal for short-duration energy storage needs, such as providing rapid bursts of power to stabilize grid frequency or to smooth out voltage fluctuations.
  - Flywheels: flywheel energy storage can quickly store and release energy in seconds to minutes, making them suitable for grid stabilization and providing backup power during transient disturbances.
- Medium-duration storage (minutes to hours):
  - Electrochemical battery technologies: they include lithium-ion, sodium-sulfur, lead-acid, and redox flow batteries, and occupy a middle ground between electric and chemical/mechanical storage technologies in terms of discharge duration. These batteries have more balanced power capacity and energy capacity costs, making them suitable for applications requiring a few hours of discharge duration.
- Long-duration storage (days to months):
  - Pumped Hydro Storage (PHS): Pumped hydro storage facilities can store large amounts of energy for extended periods by pumping water to an elevated reservoir during off-peak hours and releasing it to generate electricity during peak demand.
  - Compressed Air Energy Storage (CAES): CAES systems compress air into underground caverns or storage tanks during periods of low electricity demand and expand it through turbines to generate electricity during peak demand periods.
  - Thermal Energy Storage (TES): Thermal energy storage systems store heat or cold energy in materials such as water or molten salts. They can release stored energy over several hours to days, making them suitable for applications such as district heating and cooling, as well as industrial processes.
  - Hydrogen energy storage: hydrogen energy storage involves converting surplus electricity into hydrogen through electrolysis, which can then be stored and converted back into electricity via fuel cells when needed. Hydrogen storage is well-suited for long-duration and seasonal energy storage applications.

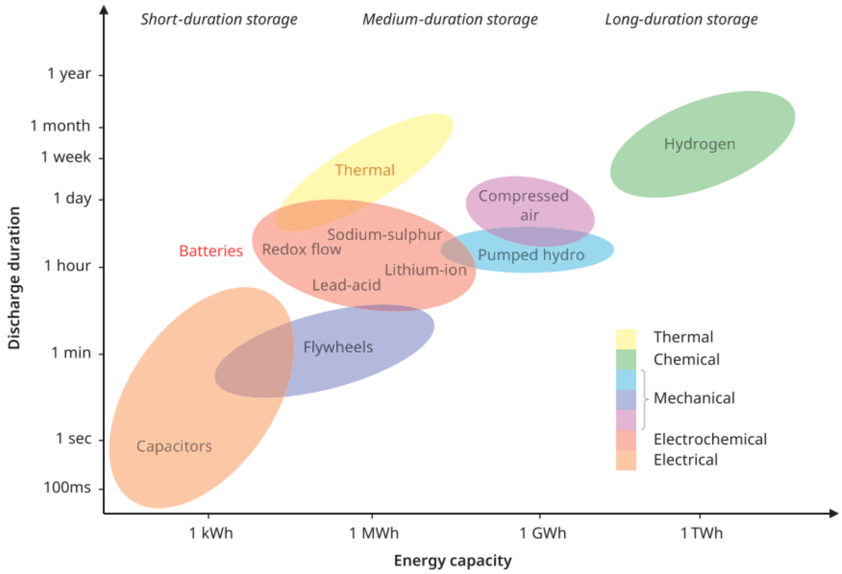


Figure 2.1: The effectiveness of different electricity storage technologies depends on factors such as discharge duration and energy capacity [53].

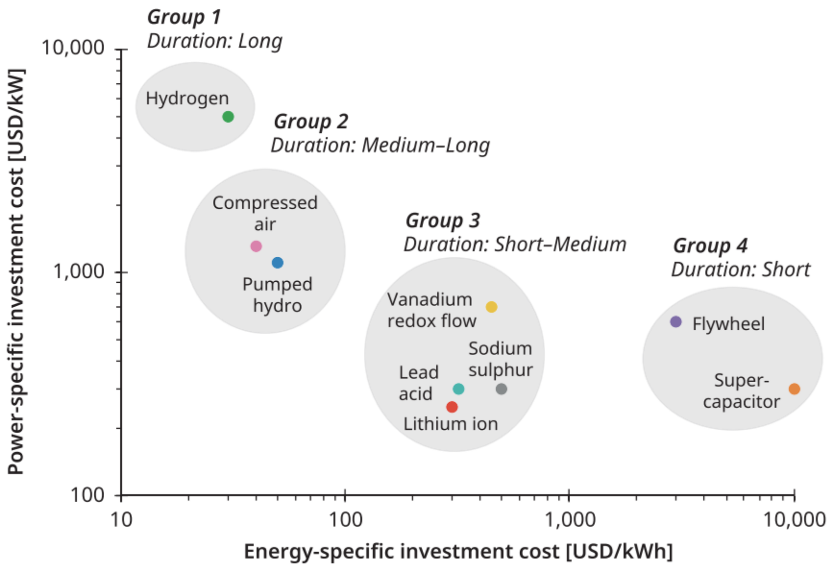


Figure 2.2: Stationary electricity storage technologies are typically categorized based on their power-specific and energy-specific investment costs[53].

This research will focus on long-duration electricity storage, presented in the following sections.

2.3.2. The Design Landscape of Long-Duration Electricity Storage

The term "Long-Duration Energy Storage" (LDES) refers to those technologies that are technically and economically able to store energy for extended periods, typically ranging from days to weeks, and are viable for infrequent use to sustain electricity production over those extended periods [54]. Defining the exact energy capacity range that qualifies as LDES presents challenges. Current literature defines LDES based on an energy-to-power ratio typically falling within the range of 10 to 100 hours or higher [55]. The system value of LDES is still a hot topic of discussion. The increased interest stems from a growing appreciation and acknowledgment of the need for “firm” low-carbon energy resources to complement variable renewable generators like wind and solar. Furthermore, the increasing frequency of extreme weather events such as fires and strong storms is driving the need for the local, clean, affordable, and resilient backup power LDES systems can provide. Batteries are useful for hourly and daily storage because of their relatively low power-capacity costs but do not provide cost-effective seasonal storage due to their high energy-storage capacity cost [56].

For this reason, LDES might be necessary for future power systems to be adequate when demand is higher than power generation for an extended period. Some literature compares the benefits provided by LDES to other forms of flexibility such as short-term storage, interconnection and curtailment. Using a multidecadal economic dispatch simulation Dowling et al. [57] analyses the dispatch patterns of LDES and compare it to one of the short-term storage technologies such as batteries in the U.S. It finds that unlike the significant and seasonal use of long-duration electricity storage for substantial inter-season energy storage, which primarily occurs during summer when solar is most abundant and wind availability decreases, batteries are regularly recharged and discharged in small amount throughout the year. In cases with the greatest displacement of firm generation and the greatest system cost declines due to LDES, optimal storage discharge durations fall between 100 and 650 h (4−27 d) [58]. In a long-term capacity adequacy study in GB, [59] finds that weather patterns extending across North-West Europe and resulting in prolonged periods of low wind during winter do not allow the adequacy of a system that relies uniquely on batteries. Similarly, Cárdenas et al. [60] agree on the fact that different storage technologies will be needed in the UK for different discharge durations to reduce the total electricity cost. Moreover, common findings in the literature show that energy storage plays a more important role as the penetration of VRE increases [61]. [61] points out that when VRE penetration is below 30%, curtailing excess energy is often the most cost-effective solution, as the surplus hours are too few to warrant storage investment. Above 80% a relatively small amount of storage is needed, while when the penetration reaches 100%, there is a substantial increase in the need for storage [61]. With growing VRE shares, the demand for storage increases linearly in terms of power capacity and exponentially in terms of energy capacity [62].

2.3.3. Technological Options for Long-Duration Electricity Storage

LDES encompasses a diverse range of technologies at varying technology-readiness levels and includes electrochemical, chemical, thermal and mechanical options. Among the main technologies that could represent a source of LDSE at a large scale are pumped hydro storage (PHS), compressed air energy storage (CAES), and Power-to-Gas-to-Power (PGP).

Pumped Hydro Storage (PHES)

A pumped hydro energy storage system (PHES) involves two water reservoirs at different elevations, where power is generated as water moves from the upper to the lower reservoir through a turbine during discharge. When electricity demand is low, excess electricity is used to pump water back to the upper reservoir. During periods of high demand, the stored water is released, flowing through turbines that convert the gravitational potential energy into electricity. According to [61], PHES is often the first choice for energy storage due to its maturity, high efficiency (over 80% [53]), low energy costs, long lifespan, and large power capacity. The main factors that could limit this technology are the fact that its geographical location is inflexible, it requires multiple years to be built, has a low energy energy density. Moreover, the creation of water reservoirs could have negative environmental and social impacts. However, according to [61] the effectiveness of PHES may decline in Europe as climate change affects temperatures and river flow, reducing water availability and potentially increasing electricity prices by up to 30% in some regions. Moreover, a higher water footprint is not desirable, due to the increasing pressure on water availability in the years to come.

Adiabatic Compressed Air Energy Storage (CAES)

In a CAES system, electrical energy is used to compress air stored in sealed underground caverns and back-produced when required with energy recovered in a gas turbine. Low specific energy investment costs make CAES suited for long-duration energy storage applications such as storing large amounts of excess renewable electricity supply to be used later. The advantages of this technology are the low specific energy capacity cost and the long lifetime. The main limitation of this technology is the availability of caverns geographically limits cost-efficient underground CAES plants. Another constraint is the depth range for these caverns, typically falling within the 500 to 1300-meter range. This limitation results from the fact that operational pressure correlates directly with depth, which is limited by the current state-of-the-art technology of power plant components that function optimally within a pressure range of 50 to 100 bar. This presents a less adaptable scenario compared to hydrogen caverns, which can span depths anywhere from 400 to 2400 meters. [63].

Hydrogen

Hydrogen can be used directly as a final energy carrier or can be converted to e.g. methane, synthesis gas, liquid fuels, electricity, or chemicals. The technology that enables the storage of electricity in chemical bonds is the conversion of electricity to hydrogen, also called Power to Gas (P2G). The produced hydrogen can be used directly or can be further processed through methanation with CO2, and the resulting renewable power methane can then be fed into the natural gas grid [64]. Producing electricity from hydrogen can result in slightly improved conversion efficiencies [65]. The main advantage of this technology is the high energy energy density and the potential to use the existing network capacity. However, this can only be provided if underground reservoirs are used to store chemical energy. Suitable formations for underground storage are located in porous rock structures covered with impermeable caprock as well as in man-made caverns in salt rock [64]. At the same time, an additional flexible load can provide benefits to the electricity system being a cornerstone for sector coupling [66]. However, the low round-trip efficiency for re-electrification and the high investment cost for water electrolyzer represent the main barrier, together with the low volumetric energy density and the need for high compression. [61] selects 23 studies that took into consideration power and/or energy system planning problems at usually a national level and with 1-hourly temporal resolution and analyses the techno-economics characteristics of P2G. According to this study, P2G is to be seen as an option to deal with the power surplus rather than a technology to satisfy the current gas demand sustainably. The reason for this is that due to its low efficiency and relative sizes of the electricity and gas sectors, satisfying the gas demand with P2G would require at least three times the current power installed capacity, representing a large cost and providing a large budget that could be used another way to fulfill the same purpose.

The following table summarised the findings discussed above:

Table 2.2: Advantages and disadvantages of the main technologies used for long duration electricity storage

Technolog	Category	Advantages	Disadvantages
PHES	Mechanical energy storage	+ Technical maturity + High round-trip efficiency (higher than 80%) + Low specific energy capacity cost + Long lifetime	- Need for suitable geographical locations - Low energy density - Long time to build - Potential environmental and societal impact of the creation of water reservoirs
CAES	Mechanical energy storage	+ Low specific energy capacity cost + Long lifetime	- Limited by the availability of caverns - Low energy density per cubic meter
Hydrogen	Chemical energy storage	+ High energy density + Potential to use existing gas networks + Potential for sector coupling	- Low round-trip efficiency (< 40%) - High investment cost - Need for compression to reach sufficient energy density

2.4. Current Challenges

As solar and wind capacity continues to expand, and economic incentives and policies are implemented to achieve 100% carbon-free grid goals, long-duration energy storage (LDES) systems could play a crucial role in promoting low-cost carbon-free electricity globally. However, each of the presented technologies has challenges related to their wider deployment. Both PHES and CAES technologies require specific geographical conditions, making their application highly site-specific and constrained to the availability of suitable sites such as heights or salt caverns. P2G suffers from conversion efficiency losses and the high costs of electrolyzers and associated infrastructure. The development of a hydrogen infrastructure for storage, transportation, and utilization remains an obstacle, together with market uncertainties related to a future hydrogen economy.

Moreover, a significant challenge for new stationary electricity systems is the conservative nature of the utility industry. Currently, only PHES and CAES systems are commercially available for bulk storage at utility scale [67]. More advanced technologies, such as electrochemical storage, are still under active development and require further utility-scale demonstration and deployment. The utility industry, which prioritizes low cost, stability, and reliability, is generally risk averse due to concerns over cost, scale-up technologies and lack of proven track record for safe and reliable long-term operation at an industrial scale [10]. Therefore, LDES will need sustained vision, development and investment strategies from both public and private sectors to become integral to a future grid that is affordable, low carbon and resilient.

2.5. Knowledge Gap and Research Question

This research stands at the intersection of resource adequacy, weather uncertainty and long-duration electricity storage.

Resource adequacy revolves around the long-term planning of power systems, ensuring they can meet future demand despite the uncertainties of supply and demand. Energy planners typically assess the power system's resource adequacy using a deterministic or a probabilistic approach and comparing the obtained metrics, such as EENS and LOLE to a reliability standard. While traditional RA assessments focus on dispatchable resources, the rise of renewable energy will cause a predominant increase in non-dispatchable and climate-dependent resources. Current literature highlights the necessity of considering multiple years to yield more accurate results. Moreover, it has identified high-pressure weather conditions, often associated with "low wind, cold snap" scenarios, as a significant source of stress on power systems. Consequently, resource adequacy must recognize weather-related events as key factors for reliability. This is for example done by ENTSO-e in the EERA [45]. However, while energy system modelers have effectively represented the impact of current weather and climate, existing resource adequacy assessments overlook the potential effects of future climate change, which could lead to increased variability in wind capacity and more frequent extreme weather events. For example, only historical data were considered for the EERA 2023 simulations, while a long-term forward-looking climate projection is foreseen from the ERAA 2024 [15].

Furthermore, there is a growing discussion about integrating flexibility options to balance wind and solar energy intermittency. Future power systems are expected to feature a blend of flexible options with complementary characteristics. There remains an ongoing debate about the required extent and form of long-duration electricity storage, compared to other flexibility options such as short-term storage or firm low-carbon energy sources such as nuclear power. Previous studies conducted in the U.S. [57] and in the UK [60] have explored the need for LDES to lower electricity costs and the risk of an energy shortfall, particularly when variable renewable energy sources make up a significant portion of the energy mix. However, no study has investigated LDES's benefits and their main drivers for a future interconnected system in Europe. This leads to the following research question:

What are the capacity value drivers of long-duration electricity storage for an interconnected European power system in 2050 in a context of high penetration of renewables and future climate?

This study aims to conduct energy assessments for an interconnected European system in 2050 where LDES is included in different cases. Weather uncertainty and the influence of anthropogenic climate change will be integrated into the analysis to provide a more accurate reflection of future climate conditions. Through a comparison of case with different levels of LDES, the research seeks to obtain insights into the potential benefits of LDES for future interconnected systems.

This research contributes to advancing knowledge in the fields of energy planning, climate adaptation, and renewable energy integration by addressing key challenges and uncertainties faced by future energy systems. Future researchers and energy planners can rely on this study to make informed decisions on infrastructure investments and optimized resource allocation, ensuring cost-effective solutions for grid reliability and resilience. Policymakers can use these findings to craft policies supporting renewable energy and storage integration in the face of evolving energy and climate challenges.

3

Methods of Approach

This research aims to evaluate the security of supply risk for a European interconnected system in 2050 and the contribution that long-duration electricity storage has in ensuring adequacy. A contemporary adequacy assessment considers uncertain factors within the system, providing a probabilistic measure of adequacy across various feasible realizations of these uncertain variables. Two approaches use probabilistic evaluation: analytical methods and Monte Carlo simulation. The analytical methods represent the system by mathematical models and use direct analytical solutions to evaluate reliability indices from the model [13]. Assumptions are often necessary to simplify the problem, especially when dealing with complex systems [68]. However, this simplification can lead to a loss of significance in the analysis [68] and, as a result, simulation techniques become crucial for accurately evaluating reliability. research uses Monte Carlo simulation, through which reliability indices are estimated by modeling the system's actual random behavior. This chapter provides a theoretical overview of this approach. In particular, energy system modeling is introduced in Section 3.1 as a way to reproduce the power system's behavior and conduct system adequacy assessments through Monte Carlo methods, described in Section 3.2.

3.1. Energy System Modelling

Energy system modeling is a useful mathematical tool that can assist decision-making about the design of the European energy system. The usual way of modeling the evolution of an energy system involves step-by-step optimization over time, typically spanning five to ten years. It starts from an existing energy system state and calculates the most cost-effective setup for the next stage while considering economic and policy constraints, such as potential carbon emission limits. Energy system models enable analysts to build cohesive scenarios depicting how energy is sourced, converted, transported, and utilized and potential shifts in these processes over time. These models have gained renewed significance as they aid in navigating the transformation of energy systems driven by climate policy.

3.1.1. Calliope

This study primarily analyzes a power system model, decoupled from other sectors, constructed using the Calliope framework. Calliope, an open-source tool, facilitates user-friendly modeling of energy systems across various scales, from local city-level systems to fully integrated continental networks. The main target for Calliope is to analyze energy systems that generate electricity from various sources, including numerous renewable technologies [69]. The key elements for Calliope are:

- **Carrier:** The energy carrier used by a technology, such as electricity, heat, or gas.
- **Technology:** An element capable of managing energy by producing, using, converting or transporting it.
- **Resource:** The origin of a technology's capability to produce, remove, or add energy to the system.

- **Location:** A node where one or more technologies can be installed. Multiple locations can be included and connected with elements called links.

In Calliope, users can also input resources, energy demand, and lists of locations and technologies. To build an optimization problem, some constraints are set by default, but users can also customize these constraints to fit their specific needs. Following the definition of input variables and constraints, the system solves a linear optimization problem for an entire year, yielding a cost-optimal configuration of the defined energy system. Figure 3.1 shows a possible conceptual scheme to represent how an energy model can be built by using Calliope.

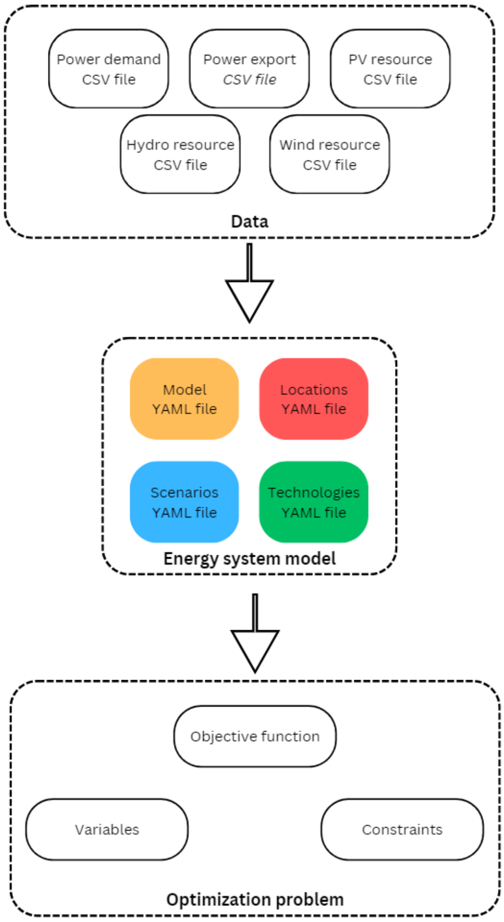


Figure 3.1: Conceptual scheme of Calliope.

In Calliope, there are three modes to run a model: **plan**, **operate**, and **spores**. The default mode is planning, where the model determines the capacities of all technologies. In operational mode, the user specifies the capacities of technologies, and the model manages the energy carrier flows within the system using a receding horizon algorithm. This approach addresses the challenge that in optimization problems, it is often not feasible to know all parameters at a specific time, but only a few days in advance. To simulate this uncertainty, Calliope employs a rolling horizon technique. The model is optimized over the complete time series in smaller parts called scheduling horizons. Each horizon is optimized for a sub-period known as the scheduling window, which is shorter than the horizon. The remaining part of the horizon, not included in the window, acts as a forecast period to provide additional information for the scheduling window. This method ensures that the optimization considers current system conditions and future forecasts.

Calliope has been used in different studies, such as examining national-scale power systems in Britain

[70], South Africa [71] and Europe [72]. Calliope is accessible on GitHub (https://github.com/calliope-project/calliope [69] and documentation is provided at https://www.callio.pe/.

3.1.2. Modelling Long Duration Energy Storage

Efficiently managing the dispatch of energy storage systems, especially for long-duration and seasonal storage, is complex due to the variability in renewable energy sources like wind and solar. These systems must address short-term fluctuations and extended periods of high and low energy production. Niet [73] highlights that optimization models are essential for balancing storage use and ensuring energy is dispatched at the right times, considering factors like storage capacity, operating costs, and the state of charge. These models must be designed to function across multiple time horizons, from daily balancing to longer-term seasonal shifts. According to [73], one of the main difficulties in modeling energy storage for day-ahead power optimization is the tendency for storage systems to be fully discharged by the conclusion of the optimization timeframe. Therefore strategies need to be implemented to prevent to encourage the optimization model in keeping optimal reserves of storage. [73] describes the main solutions used in industry to model long-duration and seasonal energy storage, which are briefly explained.

Among these solutions, one way to mitigate the issue of depleted storage at the end of the period is to expand the optimization horizon to encompass multiple days, weeks, or even months. According to [73] while this adjustment may enhance the accuracy of models for long-duration energy storage systems, it also complicates the modeling process by adding more variables and equations, which can lead to longer computation times. Alternatively, incorporating a foresight or look-ahead period can help value storage beyond the main optimization timeframe [73]. This method allows the optimization algorithm to access additional information, providing insight into the short-term value of stored energy. Typically, the look-ahead period is modeled with a coarser time resolution or fewer constraints compared to the primary optimization period to keep computational demands reasonable [73].

Another approach to managing long-duration storage is through setting end volume targets. According to [73], this method involves determining predefined energy levels, or state of charge (SOC), which the storage system should aim to reach over various time intervals—whether daily, weekly, or monthly. These targets help maintain storage capacity over time, ensuring that energy is preserved for future needs, particularly for long-duration or seasonal storage scenarios. However, the author points out that one limitation is that this approach might not fully account for operational constraints, such as transmission capacities or the availability of reserves. Additionally, introducing these end-volume targets can increase the complexity of the simulation, leading to longer calculation times[73].

Another practical method for managing energy storage operations is the stored energy value approach, as described by [73]. This strategy assigns a monetary value to the energy stored within the system, effectively determining when to charge or discharge the storage based on market prices. The key principle is straightforward [73]: when energy prices are lower than the assigned value, the system stores energy; when prices exceed this value, the system releases the stored energy. What makes this approach appealing is its simplicity and computational efficiency [73]. By basing decisions on current price signals, the method avoids the complexity of more detailed simulation models. However, as the [73] emphasizes, determining the correct value for the stored energy is critical to the success of this strategy. If the value is set too low, the storage may not be fully utilized, missing opportunities to store cheap energy and discharge during high-price periods. Conversely, setting the value too high could lead to excessive cycling—charging and discharging frequently without yielding sufficient economic benefit. Hence, accurately assessing the stored energy value is essential for balancing operational efficiency and financial returns.

3.1.3. Time Clustering

As explained in Section 2.2.2, wind and solar power generation exhibit substantial year-to-year fluctuations, making it preferable to utilize multi-decade time series data to capture the entire spectrum of this variability. Running an energy system model can be computationally intensive due to the complexity and size of the system, as well as the need to simulate multiple scenarios over long time horizons and consequently to model numerous time steps. The computational burden is often a significant challenge, particularly for high-resolution models that include detailed spatial and temporal data and involve large-scale optimization problems. Thus, there is a trade-off between reducing the computational burden and maintaining the accuracy and granularity of the model.

Time resolution reduction methods offer powerful tools to manage the computational burden on energy systems, enabling more efficient and practical simulations without significantly compromising accuracy. These methods aggregate periods with similar characteristics to reduce the number of time steps that need to be modeled. Pfenninger [31] describes three main methods to reduce a model's time resolution and assess their accuracy disparities when analyzing multi-decade time series. The approaches the author presents are downsampling, clustering and heuristic. Downsampling involves reducing the resolution of the entire time series (e.g. from hourly to every 6 hours), while k-means clustering is a common clustering algorithm used to group periods based on their similarity. Heuristic selection involves choosing days or complete calendar weeks based on certain criteria, such as selecting the week containing the maximum or minimum daily average for the given time series or choosing the week where the relative difference between time series is highest or lowest. The results of this research indicate that the different methods yield different outcomes, especially when modeling scenarios with high shares of variable renewable generation. Heuristic methods tend to be more consistent and may be more suitable for scenarios with high levels of variable renewables [31].

3.2. Monte Carlo Methods

Generating system adequacy assessment is used to evaluate the ability of the system generating capacity to satisfy the total system load. Simulation methods, including Monte Carlo techniques, are utilized to replicate the stochastic behavior of power systems. For broad assessments like those conducted at the European level, Monte Carlo simulation is the preferred method. Monte Carlo simulation employs random numbers to represent stochastic simulations, and it can be categorized into two approaches: sequential and non-sequential. In a time-sequential simulation, an artificial timeline is created to depict system components' operational and downtime periods in chronological order [74]. This is done by using random number generators along with the probabilistic distributions of component failure and restoration parameters, producing a sequence of the system's operating and repair cycles [74]. However, as non-sequential methods evaluate system states independently, they cannot account for how energy storage systems charge and discharge and they cannot track how the state of charge (SOC) evolves. For this reason, sequential Monte Carlo is the method that is used in this research.

The required number of simulations is determined to achieve an acceptable level of statistical convergence, calculated based on the standard deviation of the reliability measure [75]. Annual reliability indices such as EENS and LOLE are calculated by averaging the values of ENS and LLD obtained through the simulations until the standard error of the mean meets the selected convergence criteria. The following section outlines the method that was used for reliability evaluation: the state duration sampling approach [75].

3.2.1. State Duration Sampling Approach

The state duration sampling approach involves sampling the probability distribution of the duration of each component's state. The operating state represents when a component is up and available for service, while the repair state represents when it is down and undergoing repairs. This approach aims to generate a chronological system state transition process by combining the chronological state transitions of individual components. In this approach, the state duration distribution functions are utilized, specifically the operating and repair state duration distribution functions, which are usually assumed to be exponential. Since this approach was chosen for the research, it is described in more detail in the following subsections.

Simulation process

In practice, the state duration sampling approach is applied to simulate the up-down cycle of a two-state unit starting from an initial state by sampling the duration of each state. This method creates an artificial operating history for each generating unit, which is then used to evaluate the system's reliability indices over a specified time.

In a two-state component representation, these are the operating and repair state duration distribution functions and are usually assumed to be exponential. Initially, an initial state is allocated to every component and the duration of each component's state is sampled [75]. The duration of a component in its present state is determined using an exponential distribution based on the formula [75]:

$$T_i = -\frac{1}{\lambda_i} \ln U_i \tag{3.1}$$

Where U_i is a uniformly distributed random number between [0,1] corresponding to the i_{th} component; if the present state is the upstate, λ_i is the failure rate of the i_{th} component; if the present state is the down state, λ_i is the repair rate of the i_{th} component.
The chronological transitions of component states are simulated in this way and put together to represent the operational history of the component [75]. This approach uses the component state duration distribution functions.

Two-State Model Representation
A two-state model can represent base load units such as thermal generators, which have long operating cycles while peaking units have short operating cycles. In this case, the generating unit can be either "up" (available for service) or "down" (unavailable for service). When in the upstate, it can transition to the downstate due to a fault. Conversely, from the downstate, it can return to the upstate through repair. The generating unit model provides an artificial operating history of the unit in the state duration sampling simulation by drawing sample values of TTF (Time-to-Failure) and TTR (Time-to-Repair) of the unit. TTF refers to the duration between the start of an operation and the occurrence of a failure, while TTR is the duration taken to restore the system or component to an operation state after a failure occurs. It can be assumed that the operating and repair times of the generating units are exponentially distributed. This means that the failure rate λ of the unit is "memoryless" and constant. The Mean-Time-to-Failure (MTTF) represents the average duration until a base load unit experiences failure, while the Mean-Time-to-Repair (MTTR) indicates the average duration required to restore the unit to an operational state after a failure. MTTF and MTTR are linked to the failure λ and repair rate μ by the following equations [75]:

$$\lambda = 1/MTTF \tag{3.2}$$

$$\mu = 1/MTTR \tag{3.3}$$

Given the MTTF and MTTR of a generating unit, it is possible to sample the TTF and TTR by drawing random variates following the exponential distribution [75]:

$$TTF = -MTTF \ln U \tag{3.4}$$

and

$$TTR = -MTTR \ln U' \tag{3.5}$$

where U and U' are two uniformly distributed random number sequences between [0,1].
An up-down cycle of a two-state unit can be generated starting from an initial state by sampling values of the TTF and TTR. By combining the operating cycles of all units, the total available capacity of the system is obtained.

4 System Modelling and Analysis

After an explanation of the methods used to answer the research question, how these methods were applied in the research is described in this chapter. First, the methodology framework is given in Section 4.1. Then, the power system model that was built as part of this research is explained in detail in Section 4.2, together with the cases that were investigated. Finally, the information regarding the adequacy assessment is shown in Section 4.3.

4.1. Methodology Overview

Employing the Calliope model framework explained in Section 3.1, a linear programming model is constructed to optimize the design and operation of a possible future European power system. The model's objective function aims to identify the design and operation with the lowest total system cost, considering supply capacities, storage capacities, and transmission capacities at each node. The research was divided into two steps both using Calliope to generate different outcomes:

- **Step 1: Planning Mode:** Initially, a capacity expansion model is utilized to identify the most cost-effective configuration of generation, storage, and transmission investments and operations in 2050. Some of the inputs for this step are obtained by the Ten-Year Network Development Plan (TYNDP) [4]. The capacity expansion is done to incorporate weather variables projected to reflect the climate in 2050, as detailed in Section 4.2.5. and to endogenously obtain the power system's storage requirements. Moreover, this approach allows for the analysis of future peak net demand events across the entire period considered.
  This model ensures that national electricity demands, carbon emission targets, and a minimum of 80% share of electricity generated from RES are met. This constraint helps achieve a high share of renewables in the energy mix. It reflects the necessity for significant storage capacity beyond 80%. Moreover, a reserve margin of 0.1 for the peak demand is set. The capacity expansion model uses a greenfield approach and runs hourly simulations for ten years of weather data (1985-1995), accurately capturing the LDES characteristics needed to address seasonal variations in load and VRE generation. In this initial stage, time clustering and averaged dispatch simulations are utilized. This approach facilitates the computational feasibility of modeling a wide range of loads and weather conditions. In this phase of the research, forced outages were not included. The generated design adheres to the technical constraints of available technology components and the political constraints.

- **Step 2: Operation Mode and Adequacy Assessment** After obtaining the design of the power system, the economic dispatch was simulated for different energy storage scenarios, where the storage power capacity and the round-trip efficiencies of LDES and SDES are the same, but the duration of LDES varies from 50 to 200 hours. The simulation is done for all 8760 hours of a year using Calliope's operation mode. Forced outages for thermal generators were included. Monte Carlo simulations were conducted in this mode to obtain the load curtailment time series and calculate the EENS and LOLE for every case.

Figure 4.1 illustrates the main elements of the methodology followed in this research:

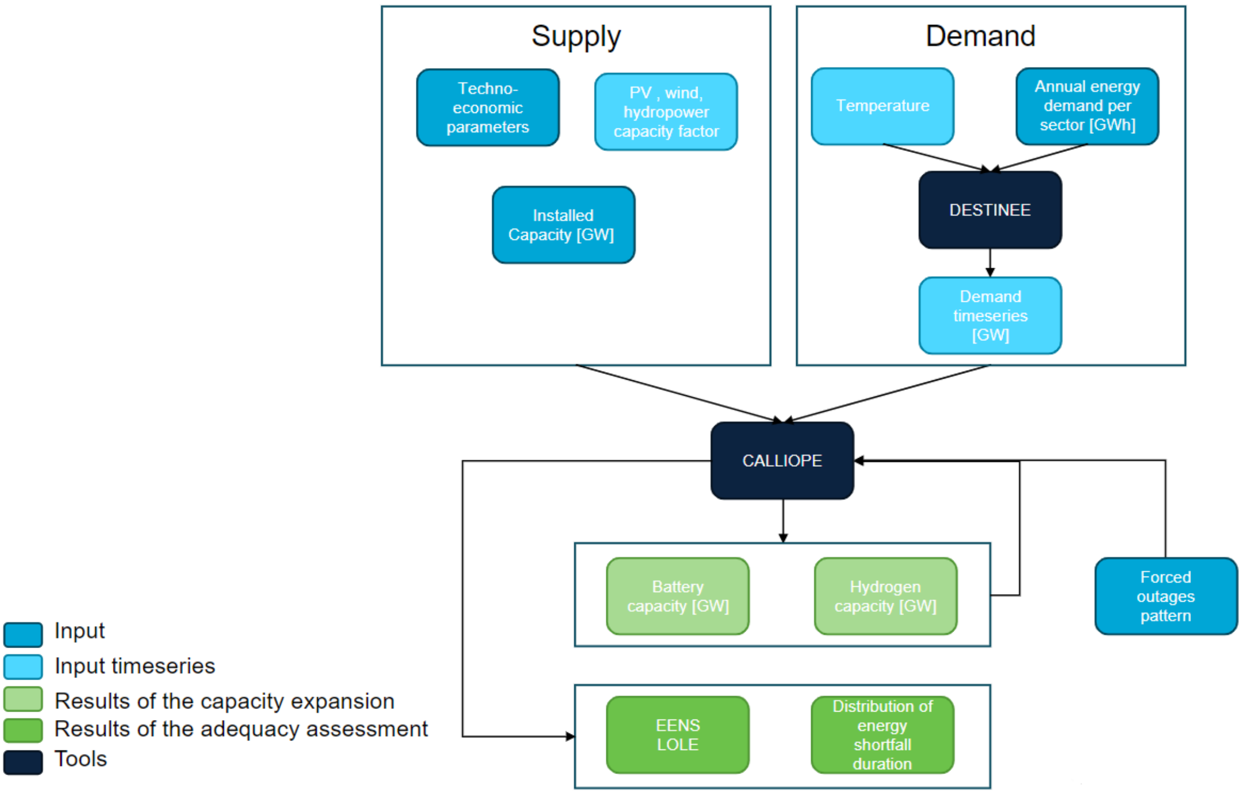


Figure 4.1: The model framework employed in this study integrates various input data (depicted in blue), obtained from different sources. Temperature-dependent demand time series were specifically derived using the DESSTinEE tool. Subsequently, an optimization problem was formulated within the Calliope framework, utilizing both supply and demand datasets. The outputs (depicted in green) represent the outcomes generated by the Calliope optimization model. Notably, the installed capacities of battery storage and hydrogen technologies result from the planning mode optimization problem. Additionally, the supply and demand time series are outcomes derived from Calliope's operational mode economic dispatch. to compute the EENS and LOLE metrics. This analysis aids in comprehending the impacts of LDES on the system's adequacy.

4.2. Model Outline

This research focuses on a future European electricity system; This system is represented as a network of nodes, each representing a European country, and the power flows between them. It considers the deployment of renewable electricity supply and storage technologies at each node and the transmission links between nodes while disregarding subordinate network nodes and distribution system power flows. The technologies implemented as sources of electricity include solar power, onshore and offshore wind power, hydro reservoir power, run-of-river hydro, biogas power, nuclear, and gas CCS power plants, batteries, hydrogen, and pumped hydro as a form of storage.

4.2.1. Model Assumptions

This model is a simplified representation of a European interconnected power system that, as any model, is based on a set of assumptions. Below is a list of the main assumptions:

- **Cost-driven dispatch decision:** Calliope allocates available resources for specified time periods, aiming to minimize overall system costs.
- **Perfect foresight:** It is assumed that renewable energy sources, thermal capacities (including forced outages), grid capacities, and demand are all known in advance with perfect accuracy. This means there are no discrepancies between forecast and actual values, allowing for optimal allocation of storage capacities throughout the year.

- **Aggregated demand by study zone:** Demand is aggregated at the study zone level, without modeling individual end-users or end-users group.
- **Demand is partly correlated to the weather and is unelastic:** Demand levels are partially influenced by weather, with temperature changes affecting the use of electrical heating and cooling devices. Demand is considered inelastic to price and remains constant regardless of energy prices.
- **RES production depends on climate:** Solar, wind, and hydropower generation are directly influenced by climate conditions.
- **Forced Outages (FO) affect only thermal generators:** Nuclear and gas power plants are subject to forced outages, meaning their net generating capacity is not consistently guaranteed.
- **Zonal Model:** The entire power system is divided into zones, with each zone representing a country. The power flow between zones is subject to transmission constraints, representing the maximum transferable electricity between zones.

4.2.2. Input Data

Building the model starts with collecting a large amount of raw input data. The latter is processed to serve as input for the scenario computations. Figure 4.1 illustrates the primary input data gathered and processed for the system's demand and generation.

A lot of the data given in input to Calliope was retrieved from the projections presented by the Ten-Year Network Development Plan (TYNDP) [4]. The TYNDP is a strategic planning document developed by ENTSO-E. It outlines the anticipated development of the European electricity transmission network. The TYNDP serves as a roadmap for identifying and prioritizing infrastructure projects necessary to ensure the reliable and efficient operation of the European electricity system. It considers factors such as integrating renewable energy sources, changes in energy demand, and cross-border electricity flows. The plan is updated every two years to reflect the latest developments and challenges facing the European electricity sector.
The scenarios presented in the report align fully with the goals of the Paris Agreement and the European ambitions for achieving climate neutrality by 2050 remaining neutral in terms of technology and energy carriers. Three scenarios are presented in the report and cover different time horizons:

National Trend scenario (NT)
The National Trend scenario (NT) is in line with National Energy and Climate Policies (NECPs, national long-term strategies, hydrogen strategies, etc.), matched with European targets. Data for electricity and gas in this scenario are sourced from TSOs, reflecting the latest policy and market developments discussed at the national level. The quantification of NT focuses on electricity and gas up to 2040.

Distributed Energy (DE)
In addition to the NT, which is aligned with national policies, ENTSO-E has developed two COP21-compliant scenarios, both aiming to reach the 1.5°C target of the Paris Agreement. The Distributed Energy (DE) scenario outlines a trajectory toward achieving carbon neutrality for the EU27 by 2050, along with a minimum 55% reduction in emissions by 2030. This scenario is driven by the willingness of society to reach energy self-sufficiency using readily accessible indigenous renewable energy sources. It involves a shift in lifestyle and a significant decentralized effort to decarbonize through local initiatives by individuals, communities and businesses, with support from authorities. This approach aims to maximize renewable energy production within Europe and substantially reduce reliance on energy imports. This is obtained by achieving a reduced energy demand through circularity and better energy consumption behavior and a focus on decentralized technologies (PV, batteries, etc.) and smart charging, and a minimal integration of nuclear power and Carbon Capture and Storage (CCS).

Global Ambition (GA)
The Global Ambition (GA) scenario outlines a route towards achieving carbon neutrality by 2050, along with a minimum 55% reduction in emissions by 2030, propelled by a global shift towards meeting the targets set in the Paris Agreement. This scenario includes the development of a wide array of renewable

and low-carbon technologies, many of which are centralized, and emphasizes the utilization of global energy trade as a means to accelerate decarbonization efforts. Economies of scale are leveraged to achieve significant cost reductions in emerging technologies like offshore wind, and the scenario also considers importing decarbonized energy from competitive sources as a viable option. In this scenario, energy demand also declines, but priority is given to decarbonization of the energy supply, focusing on large-scale technologies and the integration of nuclear and CCS.

The model constructed with Calliope does not account for decentralized technologies or smart charging; rather, it prioritizes the deployment of large-scale facilities. Additionally, it involves importing decarbonized energy from external sources, reflecting a broader, global approach to decarbonization. Due to these characteristics, the GA scenario was considered more aligned with the objectives of this research, leading to the selection of input data corresponding to this scenario.

4.2.3. Geographic Scope, Transmission Grid and System Scale

An interconnected power system was modeled for selected European countries, with the choice of countries limited by the availability of weather data that could represent future climate conditions, as detailed in Sections 2.2.3 and 4.2.5. The study area entails 8 locations (Great Britain, Ireland, France, Germany, Denmark, Austria, Belgium, Netherlands) each of which is considered to be a transmission network node. However, the model does also not account for the existing topology of the transmission system. The transmission grid is modeled as direct net transfer capacities between network nodes. The TYNDP GA scenario gives the maximum export capacity between nodes.

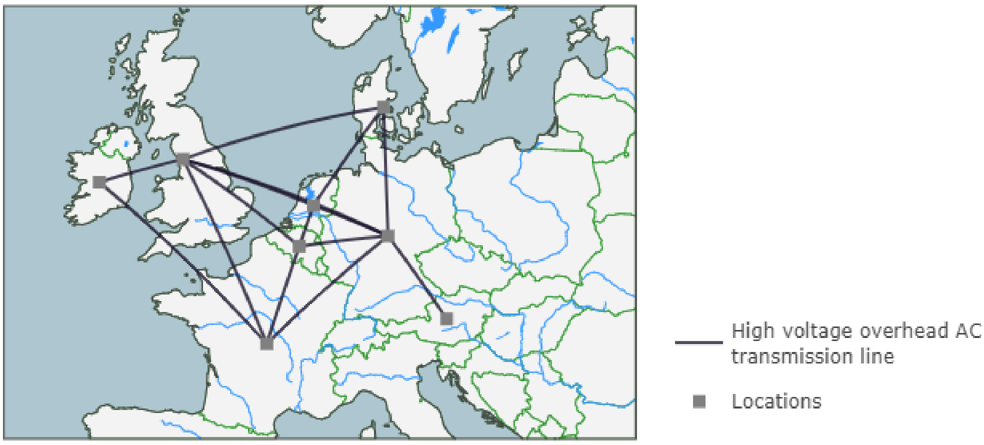


Figure 4.2: Transmission grid of the model. Each location is considered a network node and the transmission grid is modeled as a direct transfer between them.

4.2.4. Time Resolution and Horizon

For planning mode, the model uses hourly time series from 1985 to 1995 for weather variables and demand. This choice balances the need to consider multi-decade datasets to account for renewable energy variability and the need to limit the computational burden. The dataset contains "normal" weather years and particularly cold years for the geographical scope considered (1985, 1987, 1993, 1995) [30]. This approach ensures that both average and extreme weather conditions are considered when building generation portfolios. More years could have been included but this would have resulted in a larger problem size and more computational time required to solve the optimization.
To reduce the model's time resolution computational time, a heuristic model is adopted as in [31]. Using Calliope, one can apply one or more time masks, retaining parts of the time series at maximum resolution (unmasked) and reducing the resolution of other parts (masked). It is also possible to adjust the temporal scale of the extremes that are analyzed, influencing both the granularity and the type of insights that can be derived from the data, and to add symmetric padding (a fixed duration before or after the extreme values). While daily extremes can be useful for identifying the most demanding days

and planning for daily resource adequacy, finding weekly extremes can be beneficial for understanding weekly patterns and planning for longer-term resource needs. Using 10 years of simulated wind and photovoltaic (PV) generation data, the model is designed to identify five periods, each lasting three weeks, that represent the extremes of wind and PV generation. This choice is based on current research highlighting significant inter-annual variability in renewable power output [76]. Not every year experiences extreme weather conditions, as evidenced by wind droughts with a one-week duration having a return period of about two years, and those lasting two weeks occurring every five years [77]. By selecting five distinct three-week periods of minimal wind power output, the aim is to include these critical events and effectively capture the dynamics of LDES. This choice also balances computational efficiency, as increasing the number of periods would require handling more timesteps. The resolution of the remaining time series is then reduced to 6-hour intervals. This approach facilitates the long-term planning process.

For the operational mode, an hourly resolution for a one-year simulation is used. This approach enables to capture of diurnal patterns, accounts for renewable energy variability, and optimizes the generation and storage of resources. The operation of the modeled power system is optimized for a limited time horizon, called a ”rolling horizon”, taking into account a certain number of hours, usually called ”horizon”. In this case, decisions regarding operations for each 24 hours are determined by optimizing over 72-hour intervals. This procedure reduces computational burden by segmenting a large optimization problem into smaller ones and it better replicates the actual operation of the power system [18].

4.2.5. Generation

Wind and Solar Power

The available wind and solar energy is calculated based on the installed capacities of the reported technologies and wind and solar load factor profiles for each country. Future capacities installed in every country were retrieved from the projections given by the TYNDP GA scenario [78]. These capacities are given in input to Calliope as the maximum installable capacity for the optimization problem. As explained in Section 2.2.2, wind and PV capacity factors must reflect the future climate, taking into account potential variations due to anthropogenic change. [2] provides a collection of hourly times series relating to future climate projections through delta calibration. The advantage of this calibration lies in its direct adjustment of past weather events that have already been experienced. This process reduces the uncertainty associated with the variability of GMCs output, simplifying the assessment of climate change’s impact on past weather patterns. In this way, it is possible to assess what impact past events could have in the future on the power system. The datasets provide hourly data on wind speed, solar irradiation, and temperature, together with the corresponding wind and PV capacity factors. These capacity factors were estimated by using physical models that reproduced the onshore and offshore wind power curve and the PV’s power curve. These models are explained in [2] together with their performance assessment. The following subsection briefly explains the concept of delta calibration followed by [2] for the creation of the timeseries.

Integrating Historical Data for Future Scenarios

First, historical meteorological data was retrieved from the ERA5 reanalysis from 1950 to 2020 available on Copernicus Climate Data Centre [46] to create this set. ERA5 is the fifth generation of atmospheric reanalysis to be produced at the European Centre for Medium-Range Weather Forecasts (ECMWF) and currently covers the period from 1950 to the present. The dataset has a spatial resolution of 30 Km and consists of hourly 2-meter temperature, accumulation of surface solar irradiance, and hourly 10 and 100 m wind speeds. The latter was consequently bias-corrected by the author [2] to adjust the magnitude of the ERA5 wind speeds to those available from the Global Wind Atlas dataset [79]. Second, 5 climate model simulations that offered hourly climate variable output were selected and, having a higher spatial resolution than the ERA5 data interpolated onto the ERA5 grid before calibration. The climate models that were used are:

Table 4.1: Climate models used by [2]. Data retrieved from [3].

Model name	Modelling centre
MOHC-MM-1hr (ens2)	UK Met Office
MOHC-MM-1hr (ens3)	UK Met Office
MOHC-HH-3hr	UK Met Office
EC-EARTH3P-HR	European Community
EC-EARTH3P	European Community

The climate model calibration that was used is known as delta correction. Delta correction is a way to fix any mistakes or biases in climate model data by comparing it to actual weather observations. Instead of changing the climate model data directly, a model is used to predict how climate change might affect weather patterns, and then adjust historical observations based on these predictions [2]. The advantage of this type of calibration is that it directly adjusts past weather events that are already been experienced, attenuating the uncertainty related to the variability of GMCs' output. This makes it simpler to see how climate change might be affecting the weather experienced in the past. From an energy planner's point of view, this information can be used to understand how climate change might have impacted past extreme weather events, giving them insights into how to plan for similar events in the future and make the energy systems more resilient. Figures 4.3, 4.4 and 4.5 show a comparison for the Netherlands of weather variables such as temperature, wind and solar capacity factor between the historical data (ERA5) and the GCMs presented in Table 4.1.

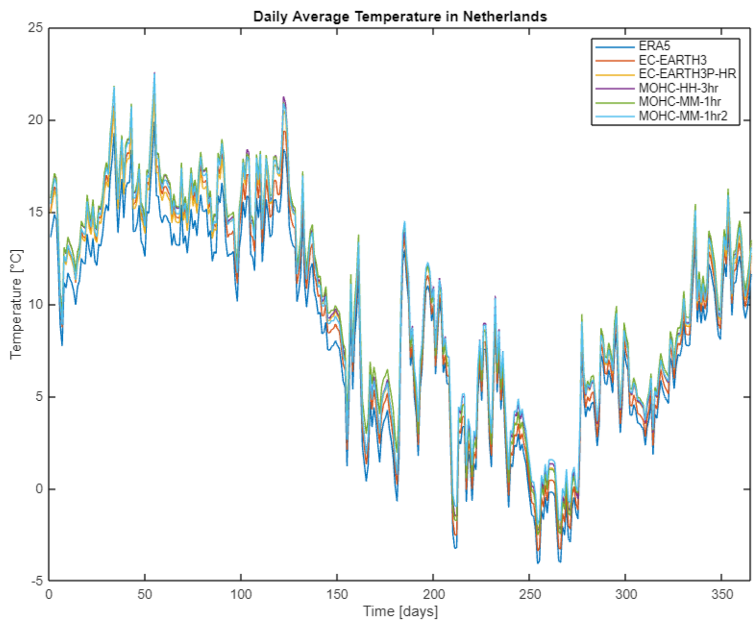


Figure 4.3: Historical and delta-calibrated average daily temperature of Netherlands for 1985. It can be noticed that temperatures are higher for the calibrated series, as expected due to the effect of climate change. Day 0 corresponds to 1st June 1985.

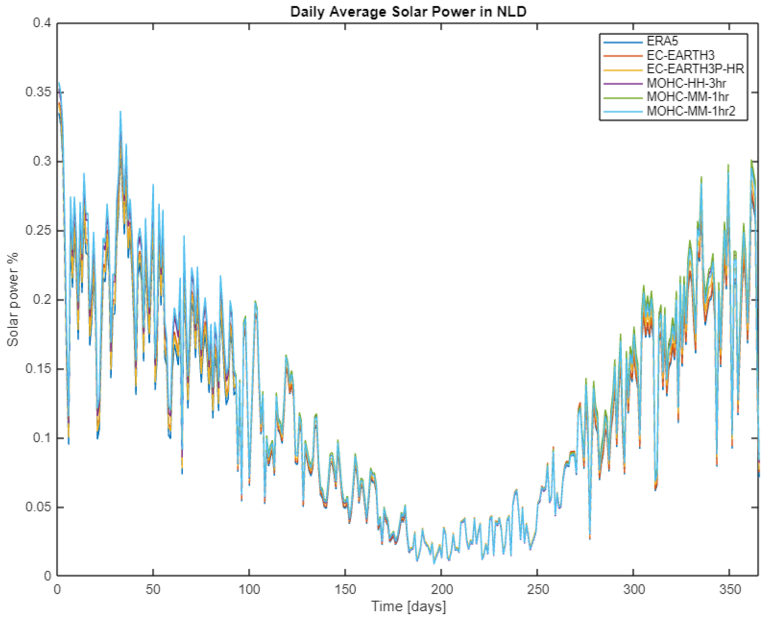


Figure 4.4: Historical and delta-calibrated daily solar capacity factor of Netherlands for 1985. The conversion from 2 m temperature and incoming surface solar irradiance to solar power capacity factor is explained and retrieved in [2]. Calibrated data appears to be on average higher than historical data. Day 0 corresponds to 1st June 1985.

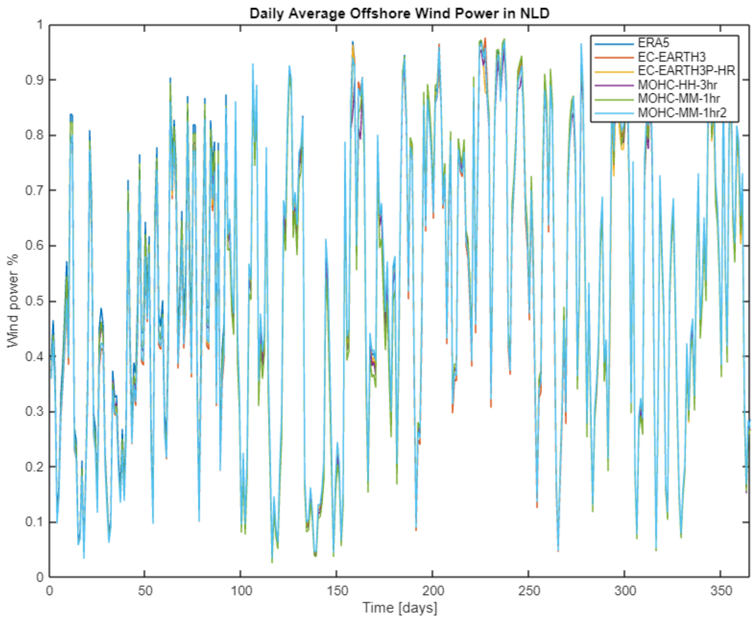


Figure 4.5: Historical and delta-calibrated daily offshore wind capacity factor of Netherlands for 1985. The conversion from 100 m wind speeds into wind power capacity factors through offshore wind power curves is retrieved from [2]. Calibrated data appears to be on average than historical data. Day 0 corresponds to 1st June 1985.

Biofuel

The primary sources of biomass for energy production are agriculture, forestry and waste. Agriculture sector energy sources are considered energy crops and residues (primary, secondary and solid). ”Energy crops” refers to the crops cultivated primarily for the production of end-use energy carriers, such as sugar, starchy and oily crops. Residues include dry and wet manure from cattle, suitable for gasification, olive pits and the waste obtained from pruning of permanent crops. Estimations of biomass potential for the year 2050 were retrieved from [80]. Based on land use, agricultural practices and proceeded areas, a low bioenergy availability scenario was assumed, therefore excluding dedicated farming for energy crops and focusing instead on residuals and wastes. The model does not differentiate between materials derived from various feedstocks, assuming a uniform combustion efficiency of 45% for all biomass sources.

Nuclear and Gas CCS

Nuclear and gas CCS technologies are likely to be considered as potential components of the energy mix due to their capacity to generate low-carbon electricity. Nuclear power is a well-established low-carbon energy source that has been part of the European energy mix for several decades. While there are concerns regarding nuclear waste disposal and safety, nuclear power plants produce minimal greenhouse gas emissions during operation and can provide a stable baseload power supply. Gas CCS involves capturing carbon dioxide emissions from natural gas power plants, and storing them underground to prevent their release into the atmosphere. Installed capacities for these technologies are retrieved from the TYNDP GA scenario. Efficiencies for nuclear power and gas CCS are set respectively at 033 and 0.53.

Hydro Run of River and Reservoirs

While hydro run-of-river power plants are modeled as a continuous supply of electricity with no storage facility, reservoirs are modeled with internal storage that provides both base load as well as the ability to be shut down and started up at short notice according to the demands of the system (peak load). The assumption that was taken is that the potentials for hydro run-of-river and hydro reservoirs are currently largely tapped, with minimal expansion potential. Therefore, hydro-generation capacities are limited to today's levels. Hydropower installed power and energy capacity data was retrieved from the JRC Hydro Power Database was utilized [81] together with the values presented in Euro-Calliope [72]. Timeseries of capacity factors per unit installed capacity for hydropower reservoirs and run-of-river hydropower plants in the studied for 30 climatic years (1981-2010) are retrieved from [82].

Pumped Storage Hydro

Similar to hydro run-of-river and hydro reservoir capacities, pumped storage hydro capacities are assumed to be largely tapped and do not allow for capacity expansion. Power and storage capacity are determined using the JRC Hydro Power Database [81] and Euro-Calliope [72]. Therefore, today's pumped hydropower and storage capacity deployment is limited. A round-trip efficiency of 78/% is assumed. Furthermore, it is assumed that enough storage options are available to ensure that the only limit is the technical potential, without additional time constraints.

4.2.6. Short-Term and Long-Term Storage

Short-term and long-term storage are assumed to be deployable in all the countries. Short-term storage is modeled as Lithium-ion batteries, while long-term storage is represented by P2G, as these technologies are expected to dominate their respective applications [83]. In its Calliope European model, Tröndle et al. [72] models short-term and long-term storage using two technical parameters: the ratio between power and storage capacity and the round-trip efficiency. This approach is followed also in this research. A round-trip efficiency of 86% is assumed for short-term storage and 40% for long-term storage [72].

In planning mode, short-term storage is limited to a maximum storage capacity of 10 hours at full power [84], while long-term storage's discharge duration is constrained to be higher than 10 hours. The capacity expansion is shaped by the assigned costs for each technology's installed capacity and energy storage. In this case, LDES has a higher power capacity cost but a lower storage capacity cost compared to the ones of the battery. These costs were retrieved by the sources cited in Section 4.2.6 and reflect the economics of storage explained in Section 2.3.1.

In operational mode, short-term storage discharge duration, also described by the energy-to-power (E2P) ratio, is fixed at 10 hours, while the E2P power ratio of LDES is set at 50, 100 and 200 hours. This is done to study the effects that storage duration has on power systems' resource adequacy. Moreover, to compare SDES and LDES based on reliability metrics such as EENS and LOLE, the analysis examines how varying the power and energy capacities of both storage types impacts these metrics. The studied cases are presented in Chapter 5.2.

Technology costs and parameters
Cost estimates for the year 2050 primarily rely on [85] [86] [83]. The cost of the technology is calculated by combining the capacity cost, annual maintenance cost proportional to the installed capacity, and the variable cost for each unit of electricity generated. For all hydropower technologies, only annual maintenance and variable costs are considered as done in [72], as it is assumed that maximum capacities are already built today, so the capacity cost of hydropower does not affect the results. Technology lifetime and an interest rate of 5% are used for all technologies to calculate the corresponding Levelized Cost Of Electricity (LCOE).

4.2.7. Electrical Load

Demand profiles for future years were synthesized using DESSTinEE (Demand for Energy Services, Supply and Transmission in EuropE) [87]. DESSTinEE is a model designed to simulate the European energy sector in the year 2050, going from the demand for energy services to the hourly patterns of electricity demand and generation. It is important to note that this model serves as a tool for examining pre-existing or user-generated scenarios for the future; it does not predict future outcomes.
The modeling process starts by taking the annual demand of each country and building up hourly profile sector by sector. The annual demand is obtained from the TYNDP GA scenario retrieved from [88]. Each country's load curve is divided into key economic sectors, including residential, commercial, agriculture, industrial, road and rail. Within each sector, built environments are further segmented into space heating, water heating, cooling and other appliances. Daily profiles comprising 24 periods are defined for each sector and end-use, incorporating variations for summer/winter and weekday/weekend patterns to reflect fluctuations in human and economic activity. The model generates annual profiles spanning 8760 periods for each sector, with space heating demands adjusted based on the number of Heating Degree Days (HDD) experienced. The temperature that is given in input is the same that is used to model the power generation, so the demand is temperature dependent, as shown in Figure 4.6. Each profile has a mean and standard variation for 24 hourly values. Stochastic variation is introduced to each profile by randomly fluctuating within this range to simulate the inherent variability of human behavior. and the sector profiles are aggregated to derive the national load profile. Together with the input that is given to DESSTinEE, this framework captures four main factors shaping demand: fluctuations in electric heating demand driven by temperature variations, shifts in the technology mix for heating and transportation, sectoral changes such as improvements in efficiency, and year-to-year variations in weather conditions.

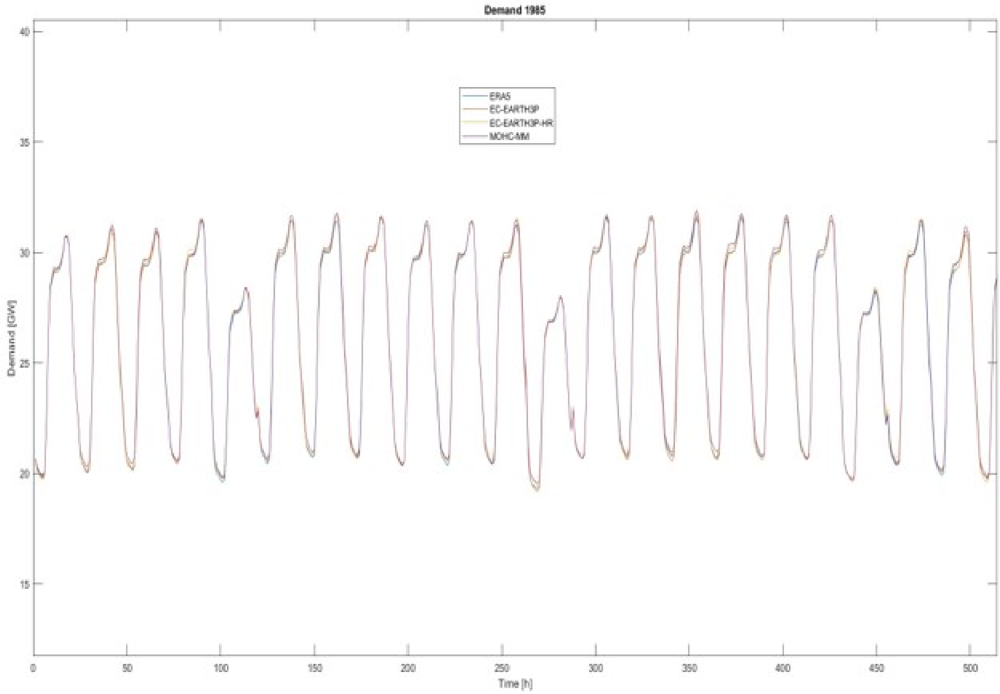


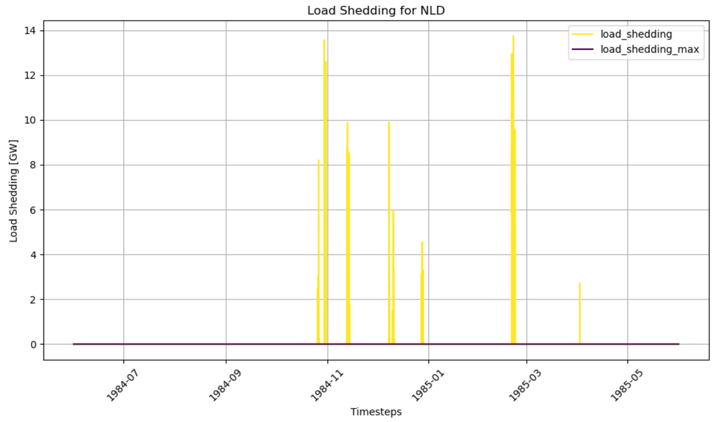
Figure 4.6: Historical and delta-calibrated demand timeseries of Netherlands for the year 1985. As the temperature is higher for the different GMCs, so is the demand needed for cooling in the summer period Day 0 corresponds to the first hour of the year.

Load Curtailment
Calliope allows the creation of a variable of unmet demand in the optimization to capture any mismatch between supply and demand. This variable is assigned a very high cost, ensuring it is only utilized when necessary. However, load curtailment is implemented in the model as a supply technology with a variable cost corresponding to the Value Of Lost Load (VOLL). This approach allows for more flexibility, as this cost can be easily adjusted.

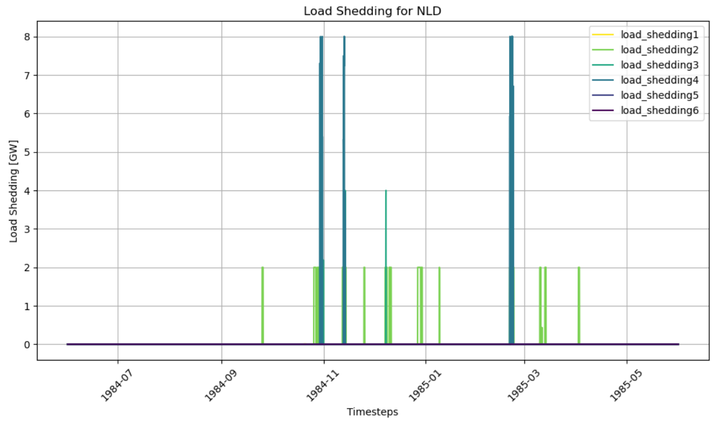
VOLL is affected by several factors, such as the type of customers, geographic location, timing, severity, and duration of power outages [89]. According to [18], load shedding should be implemented in ”tranches” to reflect the increasing VOLL with higher amounts of load shedding. By curtailing the load in tranches, the socio-economic costs of load shedding can be minimized [18]. Additionally, this differentiated approach to VOLL allows to uniquely define the operation of energy storage during periods of scarcity, as demonstrated by [18]. Various studies report that estimates for the VoLL range from approximately 1500 €/MWh to 22940 €/MWh [90]. Therefore, a primary load-shedding technology with a cost of 9000 €/MWh is created for the planning mode. Additionally, a secondary load-shedding variable is created with a cost of 10000 €/MWh. The capacity of the primary load-shedding technology in each country is set slightly below the electricity peak demand of the respective country.

Regarding the operational mode, Calliope’s optimization aims to minimize costs. However, in certain optimization scenarios, this can lead to higher spikes in load curtailment during extreme events or system stress conditions. To balance properly the energy shortfalls among multiple countries, the model implements multiple tranches with increasing minimal cost differences (approximately 1%). Each tranche’s capacity is allocated based on proportional demand across countries, typically in increments of 10% of each country’s peak demand. This allocation structure means that the first tranche can curtail 10% of a country’s peak demand, with subsequent tranches curbing larger proportions, thereby ensuring a proportional and equitable distribution of curtailment capabilities relative to each country’s total consumption. Fig. 4.7 shows Calliope’s optimized dispatch with and without load-shedding tranches. Implementing multiple load curtailment tranches results in more frequent curtailment events with lower peaks. This approach doesn't impact the total EENS, but it can influence other adequacy metrics like LOLE.

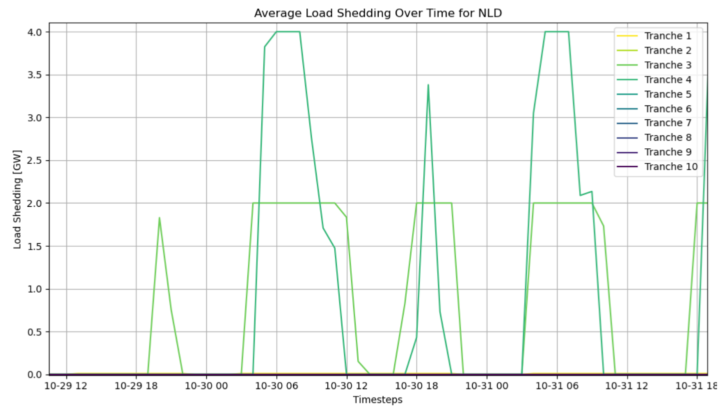
This approach assumes that proportional curtailment based on peak demand is a fair method for managing load shedding across different countries, ensuring that no single country is disproportionately affected. Additionally, the model uses a value of VOLL that is the same for every end user, without accounting for variations that might exist depending on the purpose of the electricity demand. This is a simplification, as research has shown that VOLL varies across several factors, such as customer class, location, timing, frequency, magnitude, and duration of power outages [89]. Determining the appropriate VOLL values is a complex field of research [91] that requires further attention, however, the approach used here can provide a general indication of when and to what extent load curtailment occurs during the simulation.



(a) Load curtailment distribution when only the tranches of the planning mode are used for the simulation.



(b) Load curtailment distribution when tranches are implemented. The spikes are lower as the curtailment is more evenly spread. The legend shows different load-shedding tranches, each represented by a distinct color, arranged from least to most expensive. Multiple tranches can be activated simultaneously once the tranche immediately before, and therefore less expensive, has reached its maximum load curtailment capacity.



(c) Load curtailment distribution detail when tranches are implemented.

Figure 4.7: Load curtailment implementation in Calliope's operational mode. Using multiple load curtailment tranches allows for lower peaks but a more frequent curtailment. Therefore this approach does not affect EENS but can affect other adequacy metrics such as LOLE. In fact, while the total amount of energy curtailed might remain the same, the frequency of curtailment events increases. This reflects that LOLE indicates the likelihood of experiencing load-shedding events but does not account for the severity of each event.

4.3. Adequacy Assessment

This study will be evaluated through the lens of generation adequacy assessment, simplifying the representation of the transmission grid. RA assessments are typically conducted over multiple years, as seen in the ERAA [15], to capture the inherent variability in weather that affects VRES and demand. In the planning phase of this research, multiple years of weather data were used to account for uncertainties in VRE output and demand due to annual weather fluctuations. However, for the RA assessment, only a single year is selected. This year is chosen to evaluate the impact of LDES on system adequacy under a worst-case scenario. As a result, the calculated EENS is a year-specific metric. This approach reduces the number of simulations required for statistical for statistical convergence. While focusing on a specific weather year can offer deeper insights into how weather influences periods of power system stress [92], it also introduces less uncertainty into the model by not considering all available weather years.

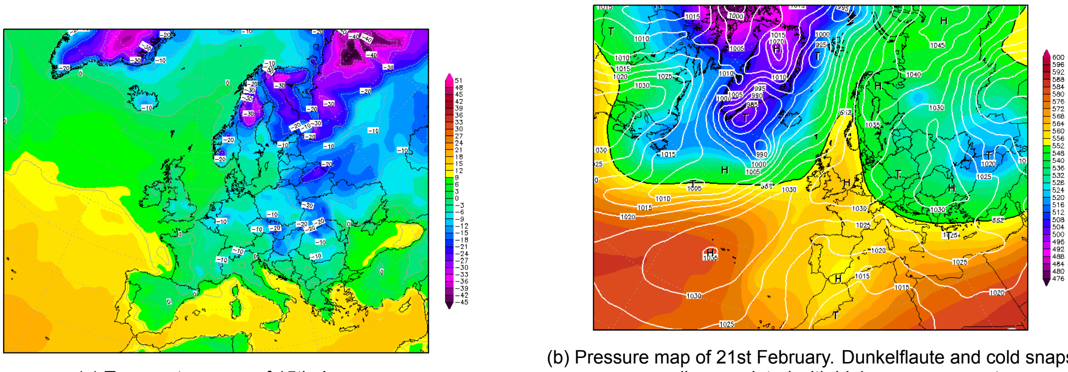
The methodology that was followed in this research uses sequential Monte Carlo simulations to model individual unit-level thermal outage states, as explained in Section 3.2.1. The scenarios used for the assessment are obtained considering different asset-forced outage (FO) occurrences for thermal and nuclear generators. These outages are simulated using a two-state Markov model (explained in Section 3.2.1) under the assumption that outages occur independently. In contrast, the availability of VRE sources is not derived from MC simulations but is based on the weather data presented in Section 4.2.5. By combining random outage scenarios, a diverse set of potential system states is generated for the chosen year. This approach enables a probabilistic assessment of results, which is highly suitable for the dynamic nature of modern power systems.

4.3.1. Selection of Climate Year

First, a specific climate year is chosen to assess the power system. The period that was chosen goes from the 1st of June 1984 to the 1st of June 1985. The winter period in 1985 was particularly relevant because it presented a period of extreme weather conditions that significantly impacted energy demand and supply [30]. 1985 experienced one of the coldest winters in recent European history, leading to exceptionally high electricity and heating demand. The cold conditions also affected hydropower generation, as lower temperatures can impact water flow and reservoir levels [93]. The year 1985 serves as a notable example of two distinct weather phenomena depicted in Figure 4.8: a widespread cold spell across Northern-Western Europe affecting various countries, and the 'dunkelflaute,' an unusually prolonged period of low wind speeds exacerbated by a persistent high-pressure anticyclone over the North Sea. By referencing 1985, it is possible to gain valuable insights into the role of long-duration electricity storage during stress on the power system induced by extreme weather events. For this year, a dataset was created following the same approach explained in Section 4.2, containing the following data for every country in the scope area:

- Temperature-dependent demand time series
- Wind capacity factor time series
- Solar capacity factor time series
- Run-of-river and reservoir hydropower plants capacity factor

An example is shown in Figure 4.9. To prepare for potential critical events anticipated in the winter of 1985, the simulation begins in the summer of 1984. This early start allows for the charging of storage systems, ensuring they are ready to provide electricity during periods of potential adequacy risks.



(a) Temperature map of 15th January.

(b) Pressure map of 21st February. Dunkelflaute and cold snaps are usually associated with high-pressure events.

Figure 4.8: Extreme meteorological conditions of 1985. Source: [1]

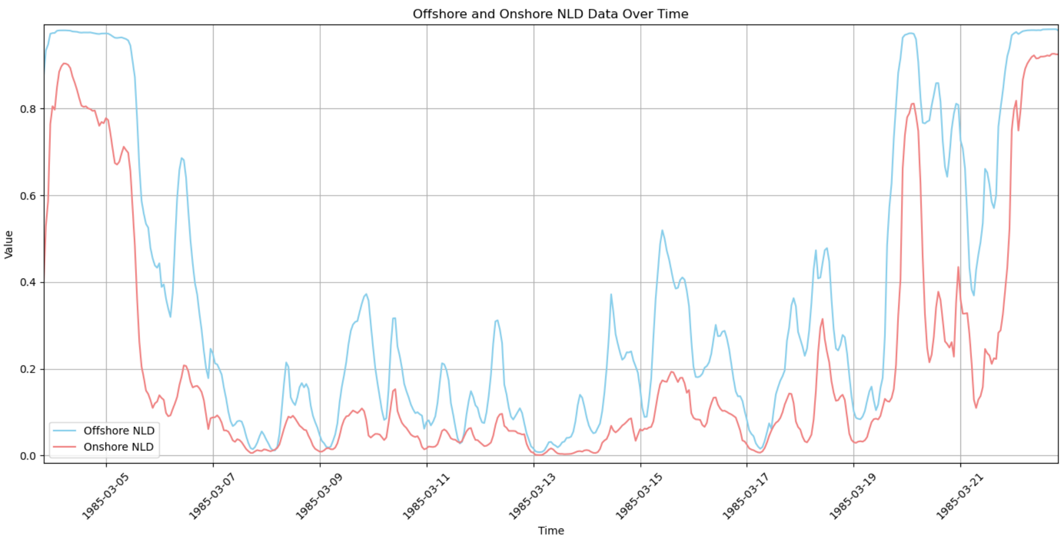


Figure 4.9: Onshore and offshore wind capacity factor timeseries.It can be noticed that the capacity factor remains below 0.2 for onshore and 0.4 for offshore for several days.

4.3.2. Forced Outage Profiles

As a second step, multiple sets of random FO occurrences, represented by hourly time series, are generated for this year. To model the operating history of a generating unit together with its up-down-up cycles, parameters such as MTTR and MTTF are needed. [4] provides the Forced Outage Ratio (FOR) and the MTTR that was used for EERA 2023 to model forced outages for nuclear and gas generators. FOR represents the likelihood of a forced outage and can be described by the following equation [68]:

$$\text{Unavailability (FOR)} = U = \frac{\lambda}{\lambda + \mu} : \tag{4.1}$$

where λ is the expected failure rate and μ is the expected repair rate. Combining equation 4.1 with equations 3.2 and 3.3 it is therefore possible to sample TTF and TTR by using the method described in Section 3.2.1. Table 4.2 shows the with calculated parameters:

Table 4.2: Parameters used to generate the operating history of nuclear and gas power plants. FOR and MTTF were retrieved from [4], while the rest was calculated using the equations presented above.

Parameter	Value
FOR	5.6 %
MTTR	24 hr
μ	0.04167 hr^{-1}
MTTF	404.85 hr
λ	0.00247 hr^{-1}

Every country presents a certain installed capacity of nuclear and gas power plants, given by the generation of the reference scenario, presented in Section 5.1. To create different generating units, the total installed capacity of nuclear and thermal power was divided by respectively the average size of big nuclear and gas power plants. A random initial state of up or down and forced outage patterns were created for each of these units. The figure below shows an example of the up-down-up cycles of one of these units:

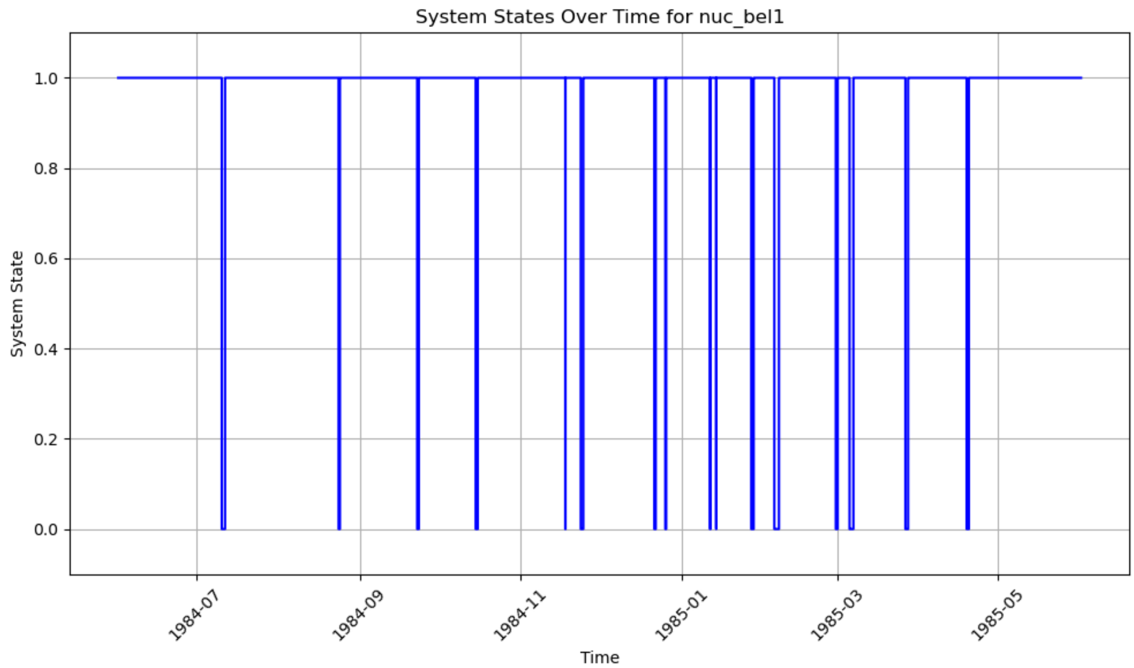


Figure 4.10: Operating history of a generating unit created for the selected year at an hourly resolution. If the unit is operating, a value of 1 is attributed to the state of the unit, while it is undergoing an outage, a value of 0 is given to the state. The initial state is randomized for each generating unit of the model.

The number of forced outage samples used for the adequacy assessment was determined only after the model reached convergence, as explained in Section 4.3.4. Each model run is performed for the selected year and includes a single instance of a randomly generated forced outage sample. Combining the selected year and M FO samples for this year yields a total of M model runs, for which it is possible to calculate probabilistic resource adequacy metrics such as EENS. Each of these model runs is optimized individually.

4.3.3. Storage Model Configurations

According to [73], the challenge of scheduling storage dispatch over time is equally complex for both long-duration and seasonal storage systems. Section 3.1.2 explains the main methods that are used to model LDES dispatch in literature. As explained in this section, an incentive needs to be given to prevent hydrogen from being depleted by the conclusion of every optimization horizon. As every approach has its own benefits and disadvantages, different strategies are implemented and evaluated in this research:

- Discharging is minimized by assigning a high cost to electricity production from LDES, with a foresight window of 72 hours.
- Discharging is minimized by assigning a high cost to electricity production from LDES, with a foresight window of 200 hours.
- Discharging is discouraged by imposing a high production cost for LDES, while LDES and battery charging are incentivized by assigning a negative cost to the electricity used for charging.

A high production cost is assigned to LDES to ensure that, in the merit order, it is the last technology to be dispatched, only being utilized during times of energy shortages. To achieve this, the production cost is set higher than that of other generators and storage technologies, but still lower than the cost of shedding load. Specifically, since the first tranche of load shedding is priced at 10,000 €/MWh, LDES is assigned a production cost of 1,000 €/MWh. This positions hydrogen as a peaking resource, deployed when net demand is high. In the final strategy, battery and LDES charging are incentivized by assigning a negative cost to the electricity consumed during charging. This effectively means these technologies earn revenue for charging, encouraging their use. The negative cost must be small enough to prevent excessive charging, but large enough to have an impact. After multiple tests, it was found that a minimum value of around 1e-10 €/MWh is required to trigger this effect. Since batteries are needed for daily electricity supply, their charging is prioritized over LDES. As a result, the negative charging cost is set at 0.9 €/MWh for batteries and 0.5 €/MWh for hydrogen.

4.3.4. Calculation of EENS

By aggregating the load-shedding tranches that are obtained from the dispatch, it is possible to calculate EENS by using Equation 2.1. The standard deviation that is associated is given by:

$$\sigma^2 = \frac{1}{N(N-1)} \sum_{i=1}^{N} [ENS_i - EENS]^2 \tag{4.2}$$

where N is the number of runs and ENS_i is the sample value of the i_{th} run. The errors that are assigned to the calculated EENS values are given by the formula for a 95 % confidence interval:

$$\textit{Confidence Interval} = EENS \pm z\left(\frac{\sigma}{\sqrt{N}}\right) \tag{4.3}$$

Where N is the total number of samples, σ, is the standard deviation, and $z = 1.96$ is the z-score corresponding to a 95% confidence level.

FOs can affect model outcomes differently depending on the specific demand and supply conditions. For instance, a major power plant experiencing an FO may pose significant adequacy risks in high-demand and low-renewable energy production scenarios. At the same time, in scenarios with high renewable energy production, the impact of such an FO may be less significant. Therefore, the results of model runs can differ significantly based on these factors. To ensure the reliability of the outcomes, the influence of additional MC simulations on the results should be minimal. The simulation should be concluded once the estimated reliability indices reach a predetermined confidence level. The purpose of implementing a stopping rule is to strike a balance between the required level of accuracy and the computational effort needed. The coefficient of variation derived from the ENS on the entire geographical scope is used as the convergence criterion in the Monte Carlo simulation. It is defined as:

$$\alpha = \sigma / E(X) \tag{4.4}$$

where $E(X)$ is the estimated expectation of ENS and σ, is the standard deviation.
The stopping rule used is the following: the simulation stops after reaching a predetermined number of samples, at which point the coefficient of variation is assessed for acceptability. If the coefficient of variation does not meet the desired criteria, the number of samples can be increased to improve accuracy. The coefficient of variation α is kept below 2%.

5 Results

This chapter introduces the key results of this research, focusing on the performance of LDES in ensuring resource adequacy. It will analyze the generation and storage capacity expansion results in Section 5.1, the impact of different LDES dispatch modeling approaches in Section 5.2, and how variations in LDES discharge duration affect the system's ability to meet electricity demand in Section 5.3. Moreover, a comparison of the performance of LDES with SDES in different scenarios is explained in Section 5.4. Through this chapter, the aim is to understand the role of LDES in future power systems, especially in high-renewable penetration contexts.

5.1. Generation and Storage Capacity Expansion

This section presents the results obtained through the first stage of this research, the planning mode, for which a period of ten years (1985-1995) was considered.

Figure 5.1 presents the total generation capacities for all renewables and fossil-fired technologies projected for 2050. The countries with the highest energy capacities are France, Germany and Great Britain. The total VRE capacity is projected to be 1225 GW, primarily from photovoltaic (546 GW), offshore wind (353 GW), and onshore wind (305 GW). Gas CCUS contributes to the generation mix by adding 57 GW. In terms of annual electricity generation, offshore wind is expected to produce 690 TWh, PV 637 TWh and onshore wind 598 TWh, representing 33%, 30 % and 28 % of the total gross electricity generation, respectively. The significant share of electricity generation from photovoltaic, onshore wind, and offshore wind sources in this scenario reflects the VRE (wind, solar and hydropower) constraint of 80% imposed in Calliope for this mode. This constraint is designed to create a system with a high proportion of renewable energy, as needed in this research. It accounts for the fact that exceeding 80% would require a substantial increase in storage capacity, as discussed in Section 2.3.2. Specifically, VREs account for of 91% power generation (1826 TWh per year), while dispatchable technologies, including biomass, nuclear, conventional hydroelectricity and gas contribute 9% (180 Twh).

It is important to highlight that VRE sources, such as wind and solar, fully utilize their maximum allowed capacity in the model's capacity expansion constraint. In contrast, other technologies, such as nuclear and gas power, do not reach their maximum potential. For example, in France, nuclear power only achieves an installed capacity of 2 GW, despite a model limit of 45 GW. This disparity may be due on one side to the prioritization of VREs and on the other side, to the greenfield approach used in the system's design. The capacity expansion model prioritizes VRE installation, driven by constraints favoring renewable energy. At the same time the greenfield approach, which designs the energy system from scratch without accounting for existing infrastructure, inherently disadvantages technologies like nuclear and gas. These technologies have higher capital costs compared to VREs and storage, making them less economically attractive.

The capacity expansion model allows for an endogenous determination of the storage capacity needed for the system, particularly hydrogen storage. This is especially challenging to calculate since hydrogen is often linked to other sectors, such as industry and transportation, complicating its role in the electricity system. Figure 5.2 illustrates the total installed energy storage power capacity for all storage options across the geographical scope. The capacity expansion is influenced by the cost that is given to each technology in terms of installed capacity and energy storage. The endogenously determined total storage power capacity amounts to 111 GW. Having the lowest installed capacity cost, the largest share comes from lithium-ion batteries, which provide 61 GW, while hydrogen storage contributes 30 GW. While the quantity, technology-specific composition, and spatial distribution of storage power vary widely across the observation area. Batteries dominate storage energy capacity for most countries but Austria, where a considerable amount of PHES is available. This is because while it was assumed that there is unlimited storage energy capacity potential for lithium-ion batteries and hydrogen storage, the technical potential of PHES can influence the storage portfolio. The optimization prioritizes the expansion of cost-effective technologies, such as PHES. When additional storage is needed to meet the 80% VRE constraint, the model will continue expanding these technologies until their technical potential is exhausted. Nearly all model regions have maximized their PHES potential. The existing capacities of PHES systems, which amount to 20 GW, are included, assuming they will not be retired by 2050 due to the long lifespan of water reservoirs. The distribution of pumped hydropower plants also reflects the availability of this technology in the territory, which depends on the altitude.

As explained in Section 4.2.6, this stage of the research required setting the discharge duration for batteries to be less than 10 hours, while hydrogen systems had a discharge duration exceeding 10 hours. In Section 5.2, the effect of adjusting the discharge duration of hydrogen, also known as the energy-to-power ratio (E2P), on EENS will be examined.

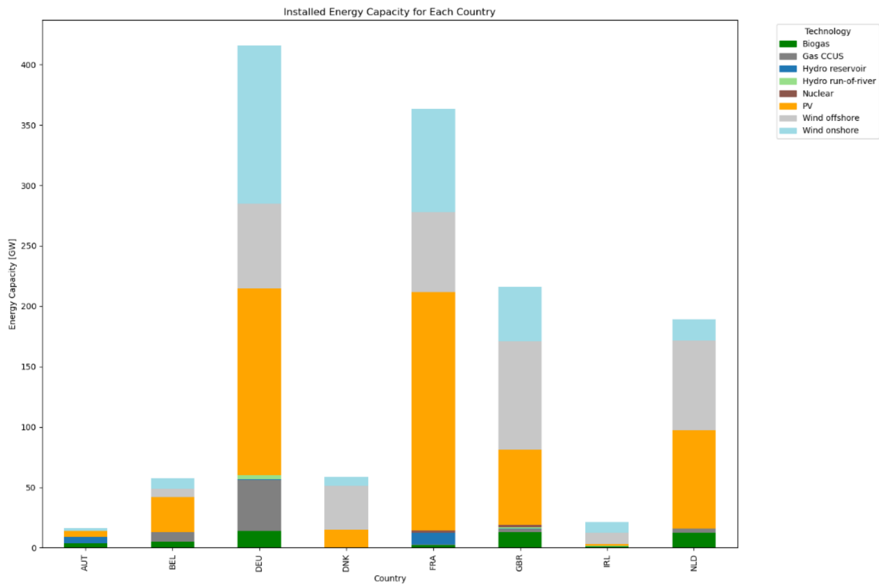


Figure 5.1: Technology-specific installed generation capacities for Europe in 2050. VRES generate 91% of the total power output, while dispatchable technologies such as biomass, nuclear, conventional, hydroelectricity and gas provide the remaining 9%.

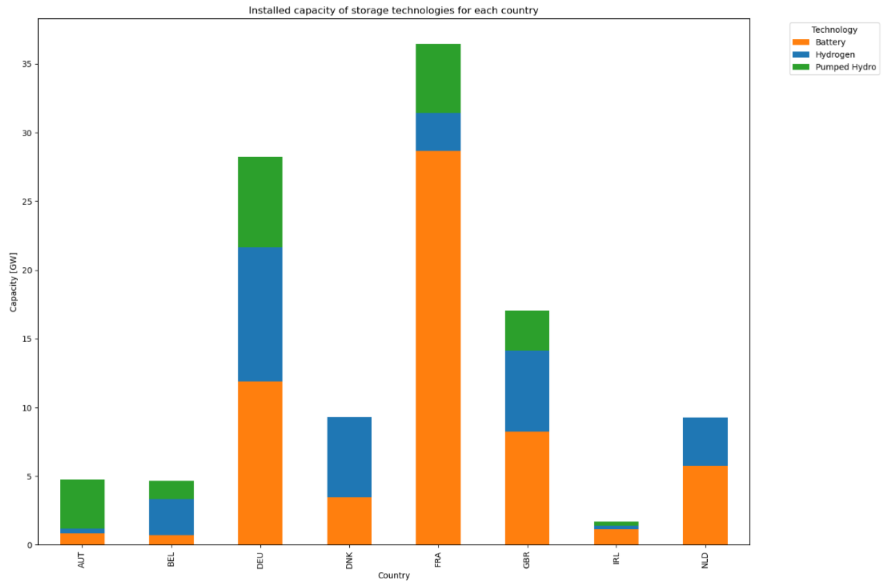


Figure 5.2: Technology-specific storage power for Europe in 205. Hydrogen accounts for the majority of energy storage capacity in most countries, except for Austria, where a significant amount of PHES is available.

Figure 5.3 shows the new transmission links and their capacities. There is considerable transmission capacity between Austria, Germany, and France and Great Britain. Germany and Great Britain also act as major hubs in the network, playing a central role in moving electricity around the region. These values correspond to the maximum installed capacities provided as input, based on projections from the TYNDP for 2050. [4].

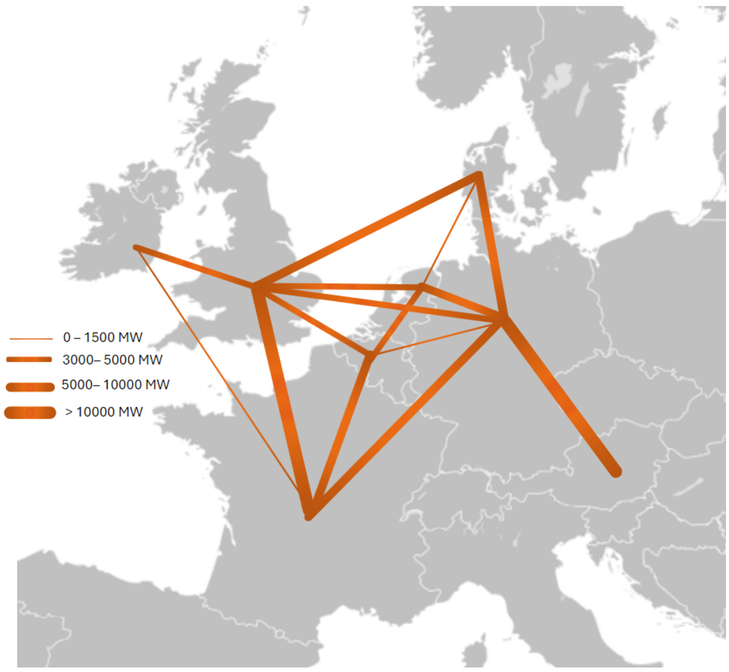


Figure 5.3: AC transmission in 2050. Germany and Great Britain serve as key hubs in the electricity network, facilitating power transmission across the region. Significant transmission capacity exists between Austria, Germany, France, and Great Britain, with installed capacities reflecting TYNDP 2050 projections [4].

Moreover, an analysis of net peak demand is conducted. Studying net peak demand hours is important for understanding the capacity requirements and operational strategies needed for long-duration electricity storage, as it helps reveal when storage systems must discharge electricity to meet high demand. Figure 5.4 shows the seasonal peak net load frequency that was done for the top 10 net load hours in each country of the scope, while Figure 5.5 shows the frequency for different years of the same events. In most countries, the top net load hours correlate to peak load hours. Within the studied period, each year contributes to at least one of the top 10 peak net load events across the entire scope of the research, whereas every country experiences at least four distinct years with the highest peak net demand hours. Given that peak net load hours occur over multiple weather years, relying on data from only one weather year when planning capacity expansions is likely to result in a system that lacks adequate capacity during operation in different weather conditions. Therefore, considering a broader range of weather data is important to ensure sufficient capacity that can meet varying demands across different years.

Across the weather years examined, the majority of the highest peak net load hours are concentrated in the winter and autumn seasons. Significant shifts in electricity demand patterns, such as increased electrification, could intensify the trend towards winter peak hours. Interestingly, none of the countries present peak net load hours in the summer season. Since summer typically lacks peak net load hours, generator maintenance and downtime will probably occur during this period. The assumption that climate change will lead to greater summer electricity needs is valid, but the risks associated with resource adequacy remain predominantly concentrated in the colder months, where demand spikes are driven by heating and reduced renewable generation. Consequently, planning for resource adequacy still prioritizes the winter season as the primary period for ensuring the reliability of power systems.

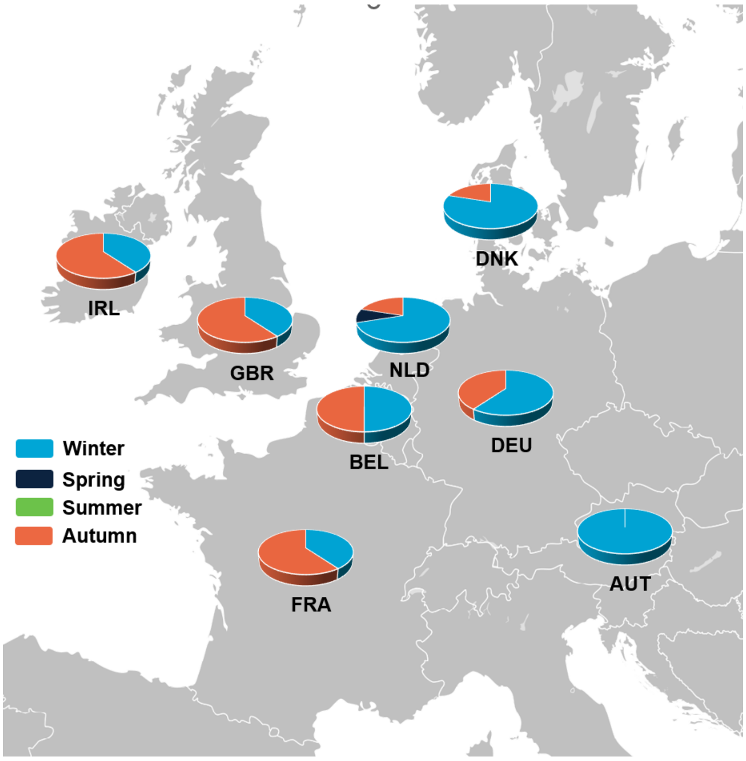


Figure 5.4: Seasonal occurrence of the top 10 peak net load hours for the resource assessment region considered. The peak net load hours are predominantly concentrated in the winter and autumn seasons across the analyzed weather years. Increasing electrification may further amplify the trend toward winter peaks. Notably, no peak net load hours are observed during the summer, suggesting that this season may be most suitable for scheduling generator maintenance and downtime.

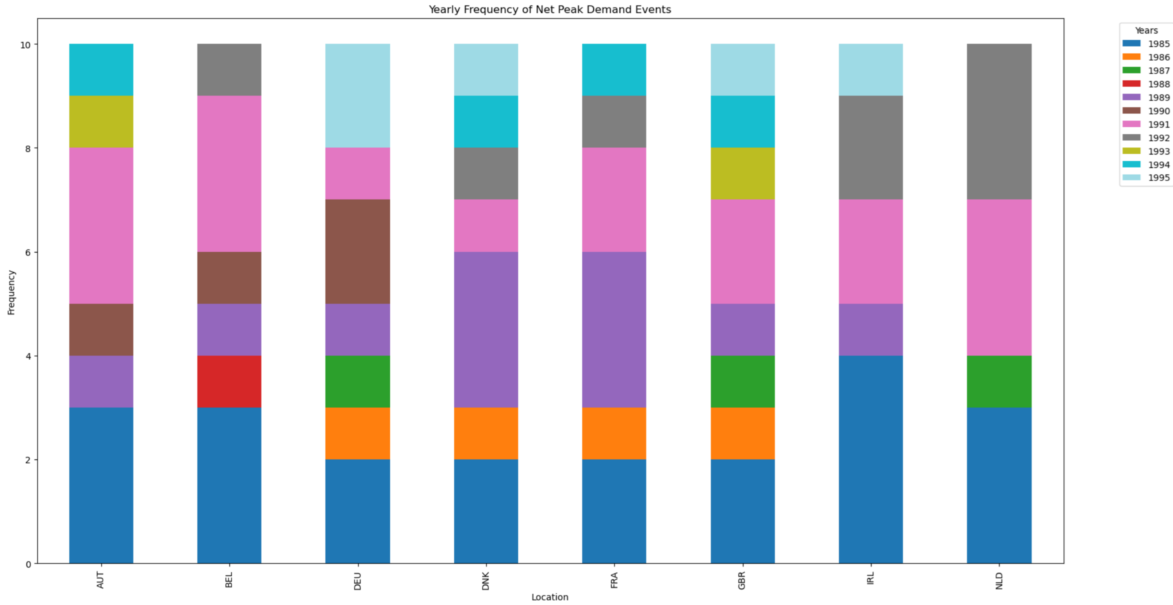


Figure 5.5: Yearly frequency of the top 10 peak net load hours for every country of the geographical scope. Every year of the considered time span results in at least one of the top 10 peak net load events when considering the entire scope of the research, while every country presents at least 4 different years with top peak net demand hours. This result underlies the importance of considering inter-annual variability when doing power system planning. Specific years appear to be more prevalent compared to others: 1985 and 1991 are present in every country, followed by 1989.

5.2. Analysis of LDES Dispatch Modeling

As described in Section 3.1.2, it is common for the storage to be depleted by the end of the optimization period. This approach is cost-effective, however, this leads to an unrealistic situation where no stored energy is carried over into the next optimization period, leaving the system unprepared for future demand. In reality, storage would need to be managed more conservatively to ensure energy availability across consecutive periods. This section compares different ways of modeling LDES dispatch and demonstrates that varying LDES dispatch model structures and initial assumptions can significantly impact results. The modeling options that are compared are presented in Section 4.3.3. EENS is calculated for each of these structures as explained in Section 4.3.4, while forced outages are implemented for nuclear and gas CCS units as described in Section 4.3.2.

To analyze storage operation, the charge levels of the storage were compared across various model structures for an LDES discharge duration of 100 hours. First, to prove the need for a strategy to regulate LDES dispatch, Figure 5.6 shows the charge and discharge cycles of hydrogen storage for the Netherlands where an E2P ratio of 100 hours is assigned to hydrogen. When no value is given to the stored energy, hydrogen cycles more frequently and is depleted by the end of the optimization horizon. In this case, hydrogen undergoes 10 full cycles throughout the year, meaning it is fully charged and depleted 10 times. As anticipated, the hydrogen reserve is exhausted early in the simulation, and despite recharging, the stored energy is not retained for potential energy shortages. The SoC remains below 0.35 and never reaches 1, as shown by the shallow cycles in Figure 5.6. This limitation may stem from the lack of an extended optimization horizon or incentives to encourage LDES charging, restricting charging to peak wind power periods. Consequently, this approach leads to under-utilization of the storage capacity, which poses risks during peak net demand periods when storage and reserves are essential. The calculated EENS value is 0.22 TWh, highlighting how this short-sighted dispatch fails to utilize the storage effectively.

Building on the previous paragraph, hydrogen must be dispatched in a way that ensures energy reserves are available during high-risk periods, conserving energy when it's not needed and replenishing reserves throughout the year. This section evaluates different approaches implemented during this research to determine the best method for meeting these requirements. The figures reveal that while both

the 72-hour and 200-hour look-ahead periods capture some elements of storage system operation, neither performs well across the entire year. In particular, the 72-hour window severely underutilizes the storage system, using only 50% of the total installed capacity. The 200-hour window better matches storage system operation during large demand swings but still does not fully utilize the available capacity. These findings are also reflected in the calculated EENS values, which show a significant decrease when moving from the 72-hour to the 200-hour look-ahead dispatch. However, the EENS values remain similar between the 200-hour look-ahead dispatch and the dispatch with discharge/charge costs. The number of full hydrogen usage cycles aligns with these findings, as summarized in Table 5.1.
In general, shortening the look-ahead period reduces the number of full storage cycles due to shallow cycling and underutilization. This implies that the look-ahead period should exceed the anticipated operational cycle of the storage system. However, for LDES, longer look-ahead periods are impractical because they significantly increase computational time and may not reflect realistic operational scenarios. The final model, which discourages discharging unless an energy shortage is imminent and prioritizes hydrogen charging after battery charging, better approximates the ideal operation of LDES. It also has the added benefit of reducing computational time.

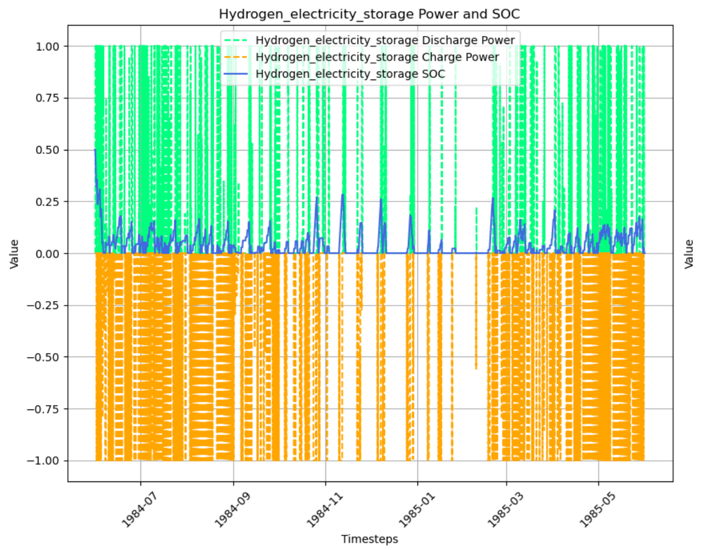


Figure 5.6: The results show that without assigning value to stored energy, hydrogen storage undergoes 10 full cycles annually but is depleted by the end of the period. The SoC remains below 0.35 throughout, indicating under-utilization of storage capacity. This is due to limited charging opportunities, which may lead to insufficient storage during high demand. The calculated Expected Energy Not Supplied (EENS) value is 0.22 TWh, reflecting ineffective storage utilization under the current dispatch strategy.

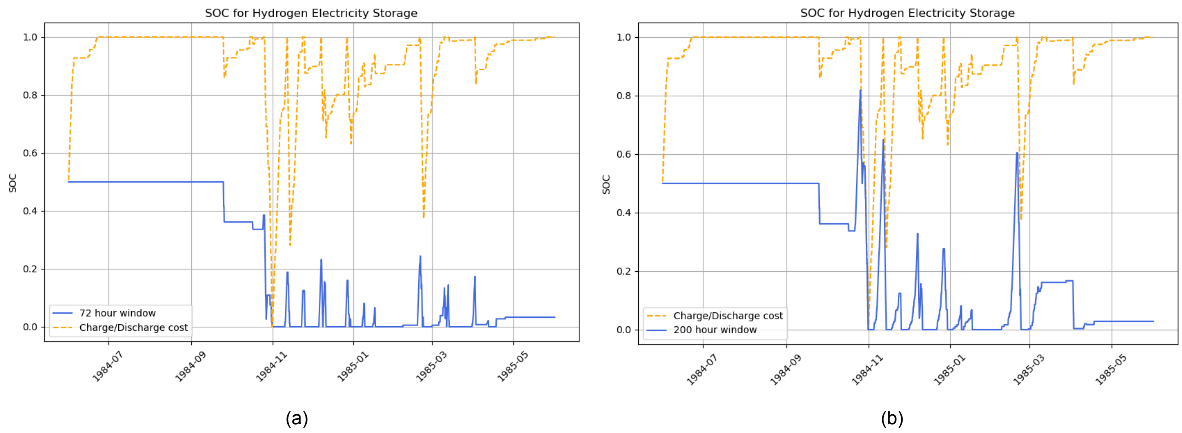


Figure 5.7: Comparison of LDES dispatch with different look-ahead windows: a) 72-hour and b) 200-hour periods, alongside a model incorporating both charging and discharging costs. Both scenarios underutilize storage, with the 72-hour window using only 50% of capacity and the 200-hour window better handling large demand swings but still falling short of full utilization.

Table 5.1: Summary of EENS values and NFC for various LDES dispatch strategies. A higher number of NFC is calculated when no dispatch strategy is implemented for LDES. This is because LDES is depleted often as there is no incentive to keep the stored energy for potential risk events. However, the absence of such an incentive leads to a higher EENS. Extending the look-ahead window beyond the expected discharge duration significantly reduces EENS. However, the most effective approach to approximate optimal LDES dispatch is to implement both charging and discharging costs for LDES, leading to lower EENS and full utilization of storage capacity.

Method	**NFC**	**EENS [GWh]**
No method	10	220
Discharge cost - 72-hour look ahead window	2	196
Discharge cost - 200-hour look ahead window	4	48 ±2
Discharge cost - Charge cost	5	35 ±2

Incorporating both discharge and charging costs resulted in a more optimal dispatch for the LDES system. This strategy is then maintained throughout the rest of the analysis. With this approach, alongside the application of FO patterns, hourly simulations were conducted to determine the least-cost operation of the interconnected power system for the year 2050. The charging of energy storage and the transmission exports are both included in the electricity loads. The system dispatch results shown in Figure 5.8 highlight the temporal patterns of generation, storage, and load. The net load, calculated as the difference between load and VRE output, displayed variations over multiple days, weeks, months, and seasons (Figure 5.9). This reveals that most periods of the year experience insufficiencies in VRE resources, causing the combined solar, wind, and hydropower generation to fall short of meeting demand. Consequently, to bridge this gap, substantial amounts of energy are released by flexible resources such as biogas and gas, which act as a baseload, and storage. The daily net load frequently fluctuates, with a mean of 6.91 GWh/day and a standard deviation of 4.69 GWh/day. The daily net load is lowest in summer and peaks in winter and spring, with significant fluctuations spanning weeks or months.

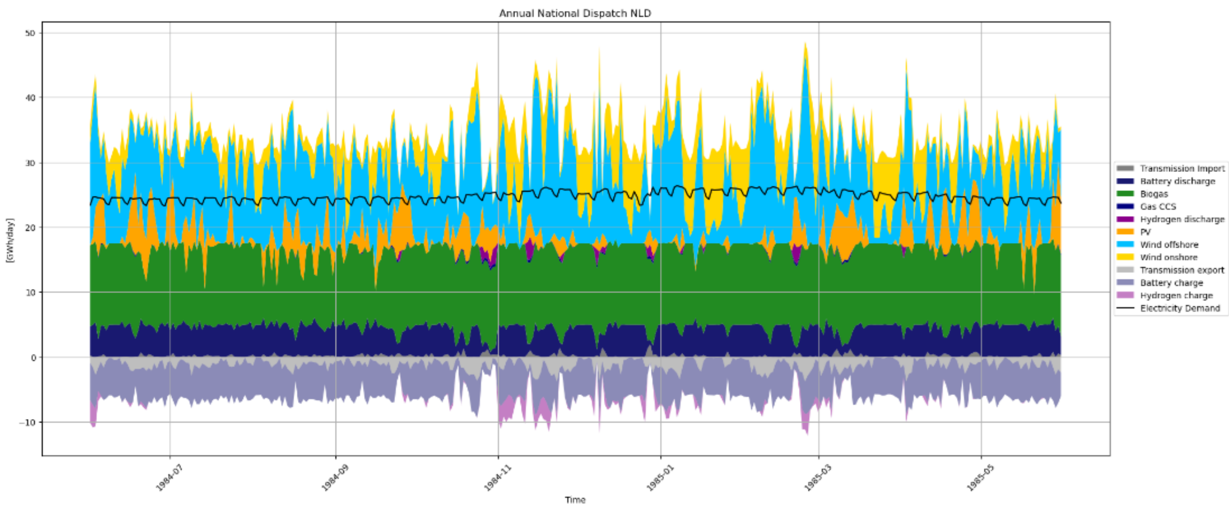


Figure 5.8: Annual national dispatch results under Scenario 1. The black solid line represents The Netherlands' national load.

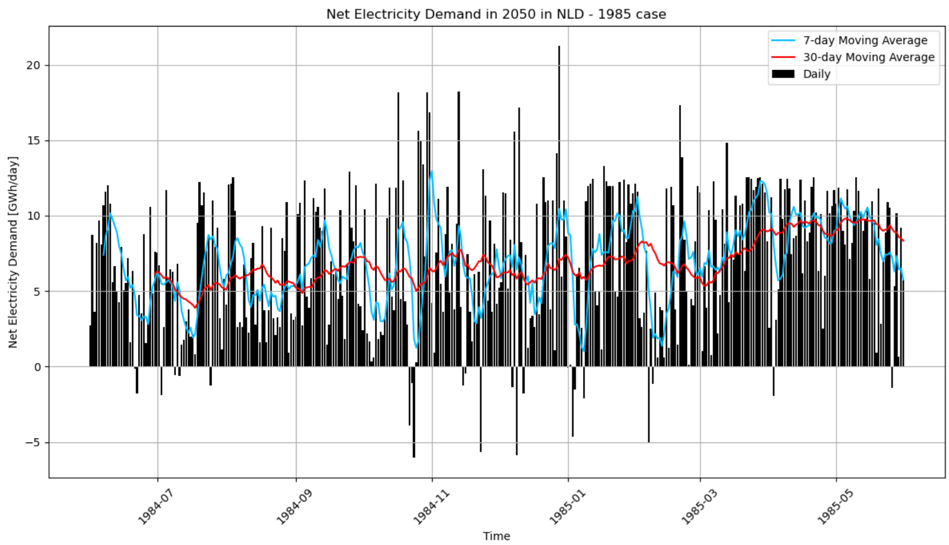


Figure 5.9: Net electricity demand in The Netherlands per day in 2050. The blue and red lines in the left figure represent 7-day and 30-day moving averages, respectively. For most of the year, VRE sources are insufficient to meet demand. To compensate, flexible resources such as biogas, gas, and storage systems release significant amounts of energy, often acting as a baseload. The daily net load varies considerably, with an average of 6.91 GWh/day and a standard deviation of 4.69 GWh/day.

5.3. Impact of LDES Discharge Duration on System's Adequacy

Section 5.1 presented the results from the capacity expansion model, which provided insights into the installed capacities of both battery and hydrogen storage systems across the countries within the study's geographical scope. As previously mentioned, the E2P ratio for batteries was constrained to less than 10 hours and similarly, the E2P ratio for hydrogen storage was also constrained to under 10 hours. In Section 5.2, the optimal method for dispatching energy stored in LDES technologies, such as hydrogen, was evaluated. This section examines the impact of varying discharge durations on the reliability of the power system, using this type of dispatch. The system operation has been simulated for different values of storage duration and the system reliability has been assessed by calculating the yearly EENS for each case. This analysis focuses on the Netherlands but could have been conducted for another country that belongs to the region considered.

First, since the beginning of the simulations, it was noted that the coefficient of variation α reached a value of 0.3 with a small number of simulations, around 40 for almost every case. This was most likely since only one weather year was considered, reducing the uncertainty of the system. The uncertainty factor in these simulations was the FOs of gas and nuclear generators. However, the generation expansion resulted in the absence of nuclear power in The Netherlands and gas power plants contributing only 2% to the entire generation. This explains the minor variability in terms of loss of load time series between one simulation and the other. This is validated by comparing this result with the loss of load of other countries that are more heavily reliant on thermal generators, such as Germany. Gas power plants represent 10% of the German generation mix. Figure 5.10 shows the load loss taking place in Germany during the same year and for two different simulations. Load is curtailed at different times of the year and with a different magnitude, reflecting two different FO patterns for the two simulations. Big load curtailment can be seen for specific periods of the year, underscoring the presence of adverse weather conditions. This suggests that weather variability will be one of the major factors of resource adequacy failures in the future [94].

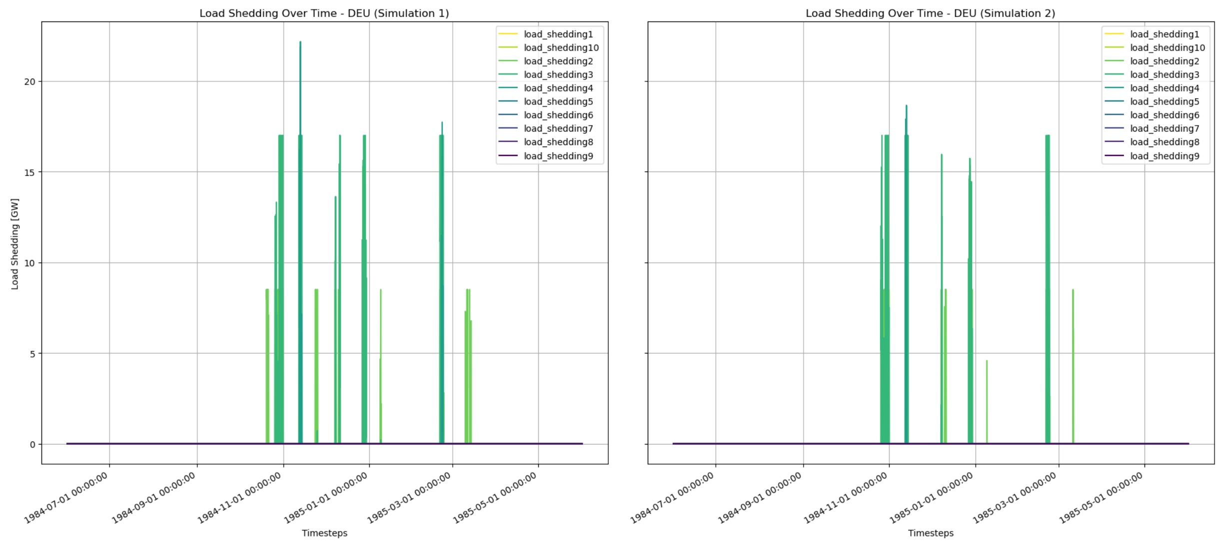


Figure 5.10: Loss of Load in Germany - Two simulations. Different colors represent different load-curtailment tranches. Comparing the two simulations, the timing and magnitude of the curtailment vary, reflecting distinct FO patterns in the simulations. However, significant load curtailment occurs during specific periods, highlighting the impact of adverse weather conditions.

Figures 5.12, 5.13, and 5.14 show the charging and discharging cycles of LDES, electricity demand, and production from various generation technologies over three weeks with multiple low wind power output periods (Figure 5.11). The Energy-to-Power (E2P) ratio of LDES is set at 50, 100, and 200 hours, respectively. From the 12th of October to the 22nd of October, and again from the 25th of October to the 1st of November, the wind is low, with significant drops on October 17th, 21st, 27th, and 30th. The phase from October 25th to November 1st results in a particularly alarming situation of the power system's reliability, as the wind capacity factor stays below 0.4 for 6 consecutive days. These days, generation sources such as biogas and gas CCUS contribute to meeting demand, supported by battery and hydrogen storage. It is noteworthy that transmission imports alone cannot provide sufficient electricity to prevent load curtailment. During periods of load shedding, the transmission network's capacity remains significantly underutilized, operating at only a tenth of its maximum capacity. This indicates that the entire power system is strained and countries are unable to support each other. Therefore, increasing transmission capacity would not mitigate load curtailment, as the overall system is under pressure.

LDES can provide power for several hours without recharging during these low-wind periods. This capability is crucial, especially during extended periods of low availability of renewable energy resources or generation capacity. Hydrogen storage typically depletes during peak demand and dunkelflaute, recharging when wind power returns. As the E2P increases, this type of storage offers firm capacity for supply reliability, assuming adequate storage capacity is available. As illustrated in the figures, extending the LDES E2P ratio helps solve some load curtailment events. Load curtailment time series, shown in the following pictures were analyzed to obtain the value of EENS and LOLE for each E2P case. In fact, while ENS provides a quantitative measure of the total energy shortfall, it does not capture the temporal characteristics of these shortages. Short-duration outages may indicate the need for flexible, short-term resources. Table 5.2 presents these calculated. It is worth mentioning that while EENS tends to plateau after 100 hours of discharge duration, LOLE continues to decline significantly. Moreover, increasing the discharge duration of LDES results in load curtailment events that last for fewer hours, as shown in the figures presented in Appendix A.1. Modeling a strictly increasing marginal cost for load shedding allows for a precise determination of both EENS and LOLE [95]. In this context, energy-limited resources are optimized to minimize LOLE [95]. The reduction in LOLE with higher E2P ratios for LDES can be attributed to the contribution of hydrogen in resolving some load curtailment events. As more energy is made available to the grid, this improvement is also reflected in the NFC values for each E2P scenario, as shown in Table 5.2. With a hydrogen capacity of 3.5 GW, as depicted in Figure 5.2, the NFC values correspond to discharge energies of 1400 GWh, 1750 GWh, and 2100 GWh for E2P ratios of 50, 100, and 200 hours, respectively.

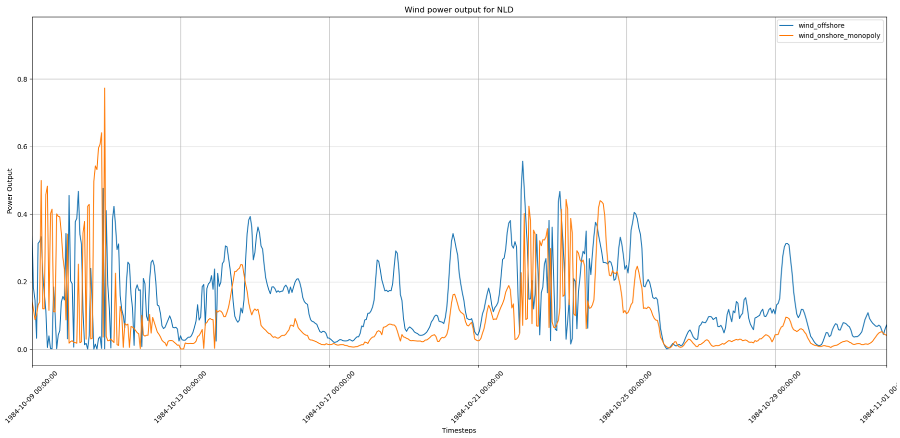


Figure 5.11: Wind power output during the 3 weeks in NLD. The values are normalized to the installed power capacity. In this period, the power output of offshore and onshore wind remains below 40% of the total generation for ten days (12th Oct. - 22nd Oct.). After a few days of increased power output (never higher than 60% of the total production), the capacity factor lowers again for 5 days (25th Oct. - 1st Nov.)

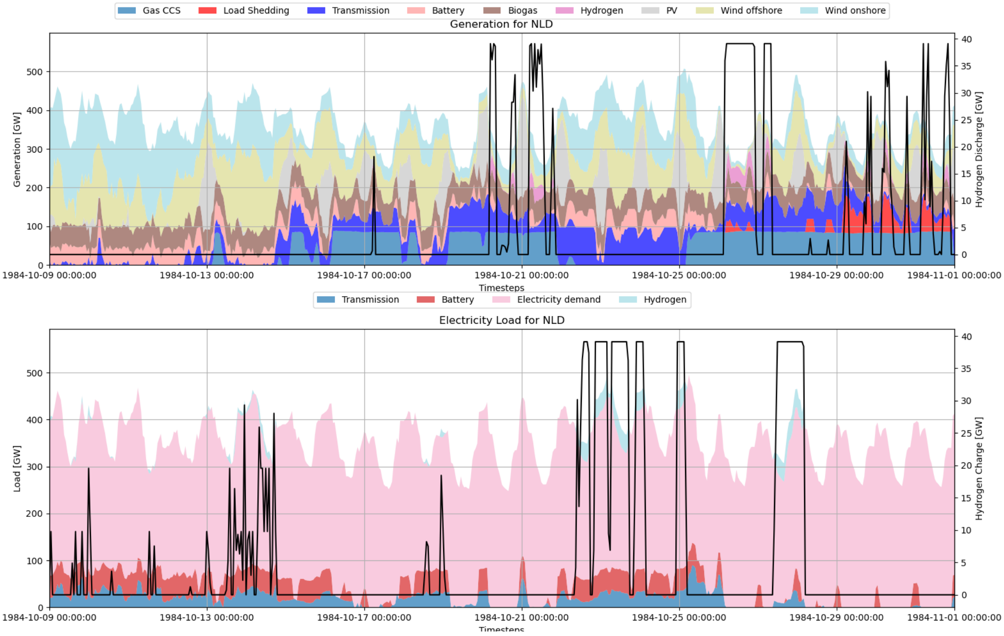


Figure 5.12: The figure shows the generation and imports (top) alongside the exports and electricity demand (bottom) for the Netherlands from October 9, 1984, to November 1, 1984. The E2P ratio is set at 50 hours. The black lines illustrate the discharge and charging power of hydrogen. During this period, load curtailment events show more pronounced peaks and a wider distribution. Notably, there are no export activities during these times.

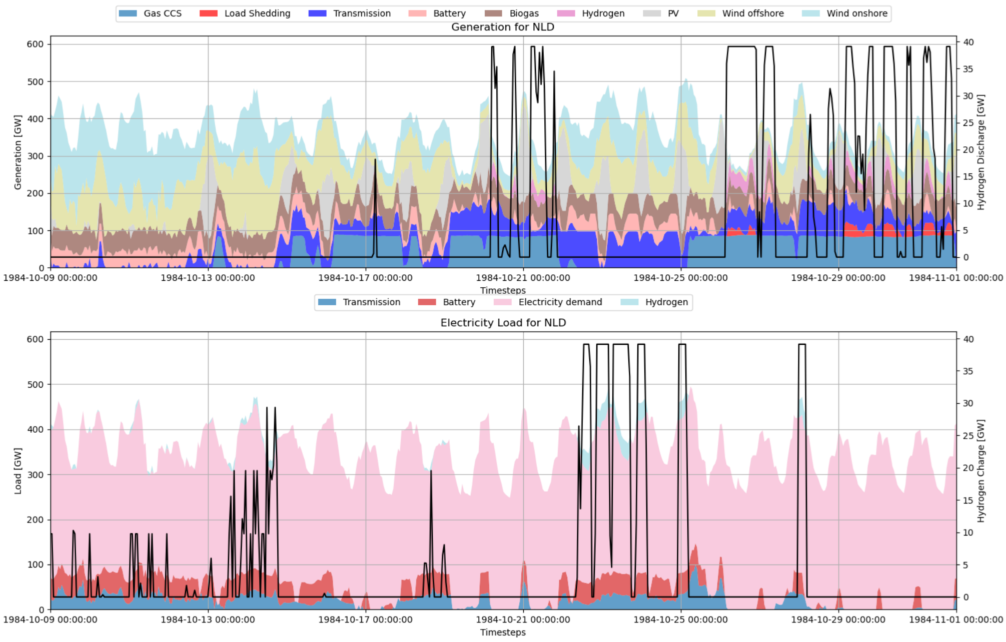


Figure 5.13: The figure shows the generation and imports (top) alongside the exports and electricity demand (bottom) for the Netherlands from October 9, 1984, to November 1, 1984. The E2P ratio is set at 100 hours. The black lines illustrate the discharge and charging power of hydrogen. In this case, load curtailment events happening on the 28th of October are solver, leading to a lower LOLE.

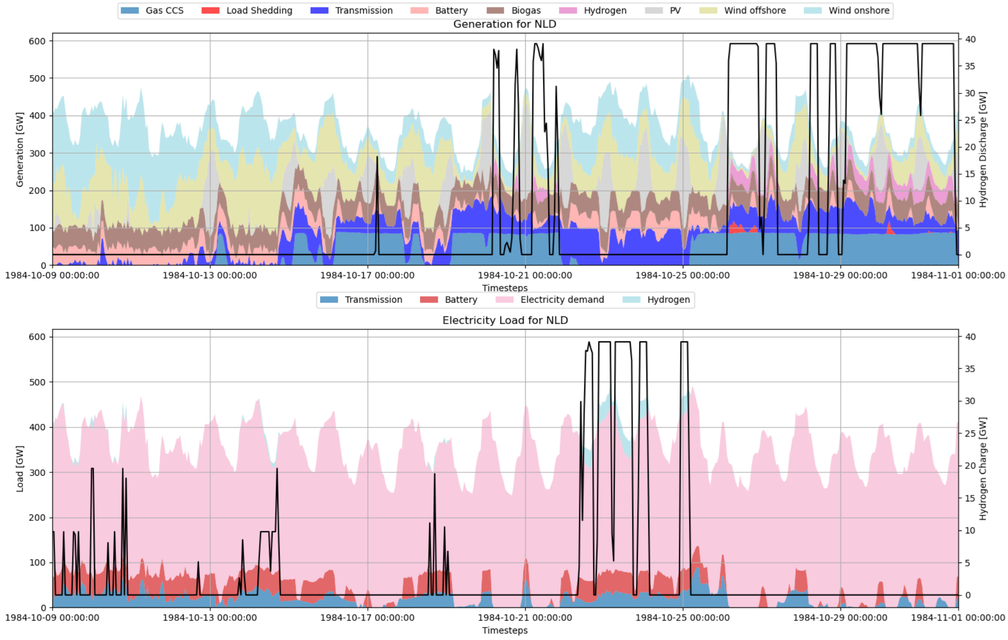


Figure 5.14: The figure shows the generation and imports (top) alongside the exports and electricity demand (bottom) for the Netherlands from October 9, 1984, to November 1, 1984. The E2P ratio is set at 200 hours. The black lines illustrate the discharge and charging power of hydrogen. In this case, almost all load curtailment events are solved, leading to a lower LOLE and allowing for exports.

Table 5.2: Calculated values of EENS and LOLE for different E2P ratios. Increasing the discharge duration of LDES from 50 to 100 hours reduces EENS considerably. The LOLE is also reduced as the dispatch of hydrogen solves some load curtailment events.

E2P [h]	NFC	EENS [GWh]	LOLE [h]
50	8	82 ±4	155 ±3
100	5	36 ±2	118 ±5
200	3	30 ±2	86 ±6

5.4. Varying power capacity, comparison with SDES

As seen in Section 2.3.2, when wind and solar power share reaches 90 % penetration in the energy mix, large, long-duration storage will be needed to meet electricity demand fully. However, the energy transition will probably go through different phases, where different technologies and flexibility options are employed. These phases, characterized by the share of low-carbon power generation, influence the required storage discharge duration [96]. In the first phase, a reduction in conventional plants—previously responsible for system regulation through generator inertia—occurs, shifting the focus to energy storage systems with durations of less than one hour. Many European countries, including Germany, are currently in this phase. For example, by 2020, more than 50% of frequency regulation in Germany was provided by batteries [97]. During the second phase, the levelized cost of electricity from renewables plus storage drops below that of fossil fuels, leading to widespread deployment of storage. Here, alternative technologies may play a stronger role due to the discharge requirements of the system. This motivates the examination of reliability metrics while varying the power and energy capacity of LDES and SDES. This section provides a resource adequacy assessment, comparing SDES and LDES based on reliability metrics such as EENS and LOLE. The analysis examines how varying the power and energy capacities of both storage types impacts these metrics.

To evaluate the effect of installed power capacity on supply security, the system's hydrogen capacity was halved, reallocating the remaining capacity to batteries. This change also altered the installed storage, linked to the installed power capacity by the E2P ratio, which is 10 hours for the case of the battery, and 200 hours for the case of hydrogen with a 200-hour discharge duration. The simulations yielded an EENS of 11 ±1 GWh and a LOLE of 100 ±2 hours. Notably, although the EENS value is lower for the E2P = 200 hours case (see Table 5.2), the LOLE value is higher. This is evident from Figure 5.15, which illustrates the magnitude and frequency of load curtailment duration for this type of dispatch. Compared to Figure A.3, load shedding peaks have been reduced, but some curtailment has shifted over time, increasing LOLE. Longer curtailment events, such as those lasting 18 or 19 hours, occur more frequently in this scenario, compared to 17-hour events in the E2P = 200-hour case. Thus, increasing installed power capacity reduces EENS but has less impact on LOLE.

To investigate whether this EENS reduction is due to increased battery power rather than storage, another scenario reduced LDES installed energy to one-fourth of its original value, with the remainder allocated to batteries. This resulted in an EENS value of 0.45 ±0.01 GWh and a LOLE of 42 ±1 hours. Figure 5.16 shows the total load shedding and its frequency distribution for this particular case. Increasing the energy storage capacity results in solving most of the load curtailment events and in reducing peak events.

By looking at these results, an immediate conclusion that could be drawn is that LDES is not necessary, as increasing the amount of energy capacity stored in batteries contributes to considerably decreasing the EENS. To understand better this point, a final test was conducted, where LDES storage capacity was halved to its original value, with the remaining part given to batteries. The simulations for this case resulted in an even smaller EENS of 0.25 ±0.1 GWh and a LOLE of 25 ±13 hours. The longest curtailment event was only 9 hours, compared to 18 hours in the previous scenario. This suggests that while battery capacity improves short-term reliability, LDES remains critical for ensuring supply security during extended periods of low renewable generation. Battery resources complement LDES by providing short- and mid-term flexibility, ensuring that LDES is only dispatched during periods when the limited discharge duration of batteries is insufficient. The reduced LOLE in cases with higher LDES capacity indicates that for prolonged low-wind conditions, batteries alone may lead to load curtailment, while LDES helps prevent shortages by providing electricity during sustained periods of low renewable output.

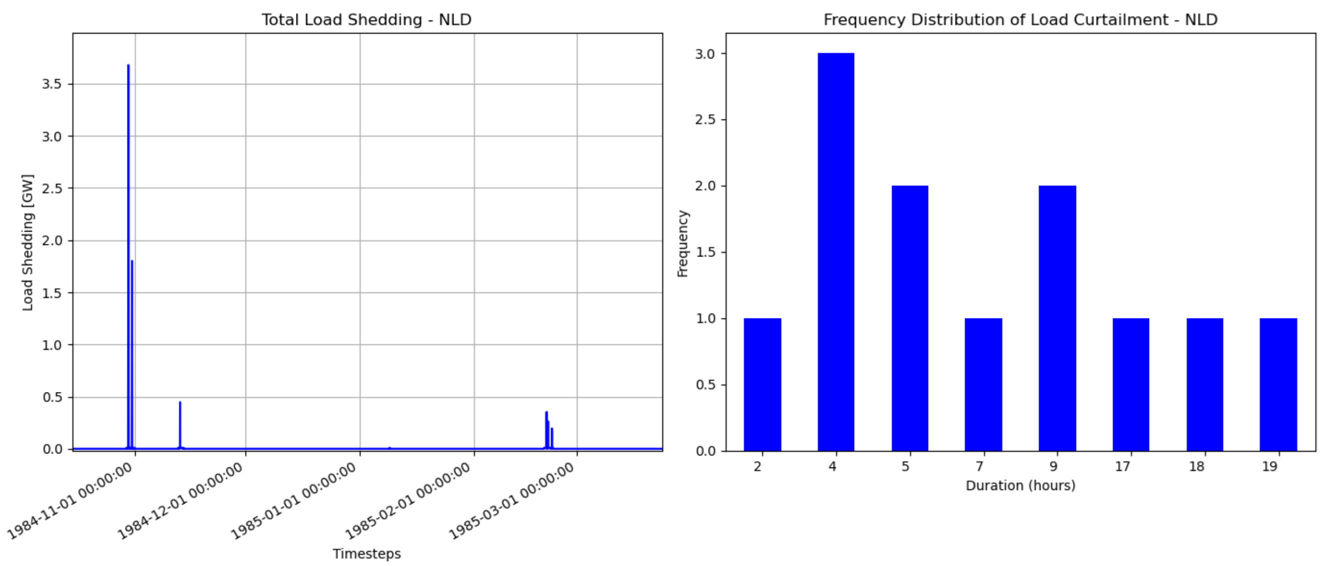


Figure 5.15: Load Shedding Distribution - Case of halved LDES power capacity. The figure illustrates the impact of halving the hydrogen power capacity and increasing battery capacity on load curtailment events. The shaved peaks and shifted load curtailment over time are visible, demonstrating the effect on EENS and LOLE. Increasing the power capacity of SDES technologies can be an effective way to decrease EENS, but not LOLE.

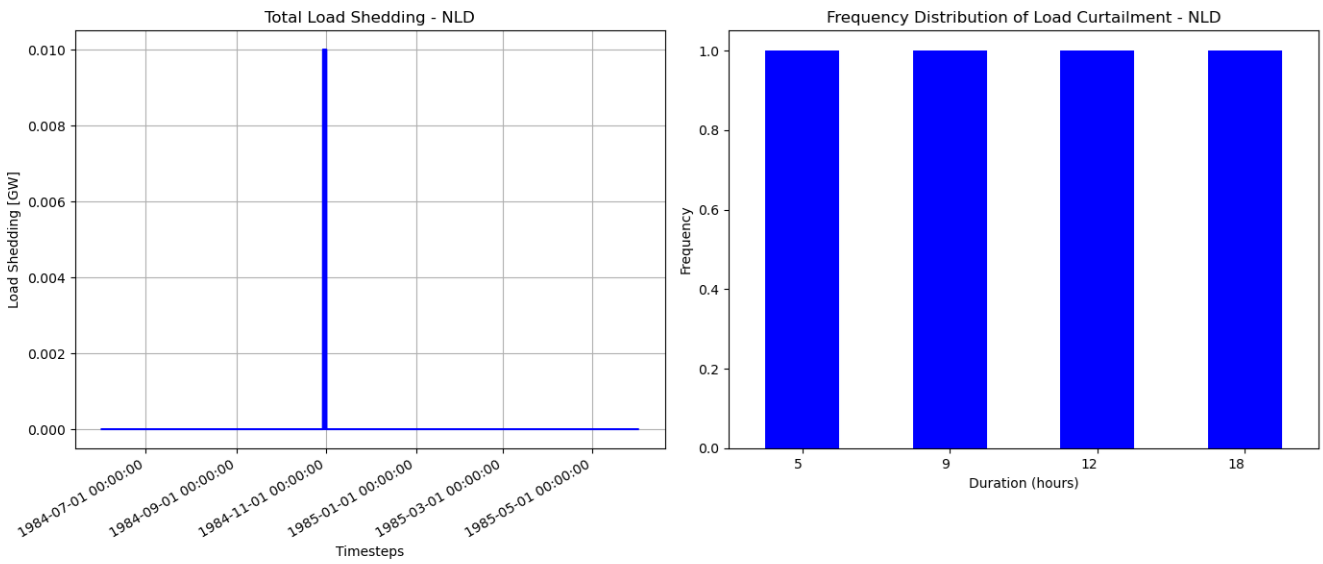


Figure 5.16: Load Shedding Distribution - Case of LDES energy capacity reduced to 1/4th. The figure shows a significant reduction in peak load curtailment, highlighting the role of battery energy capacity in reducing EENS and addressing shorter-duration curtailment events.

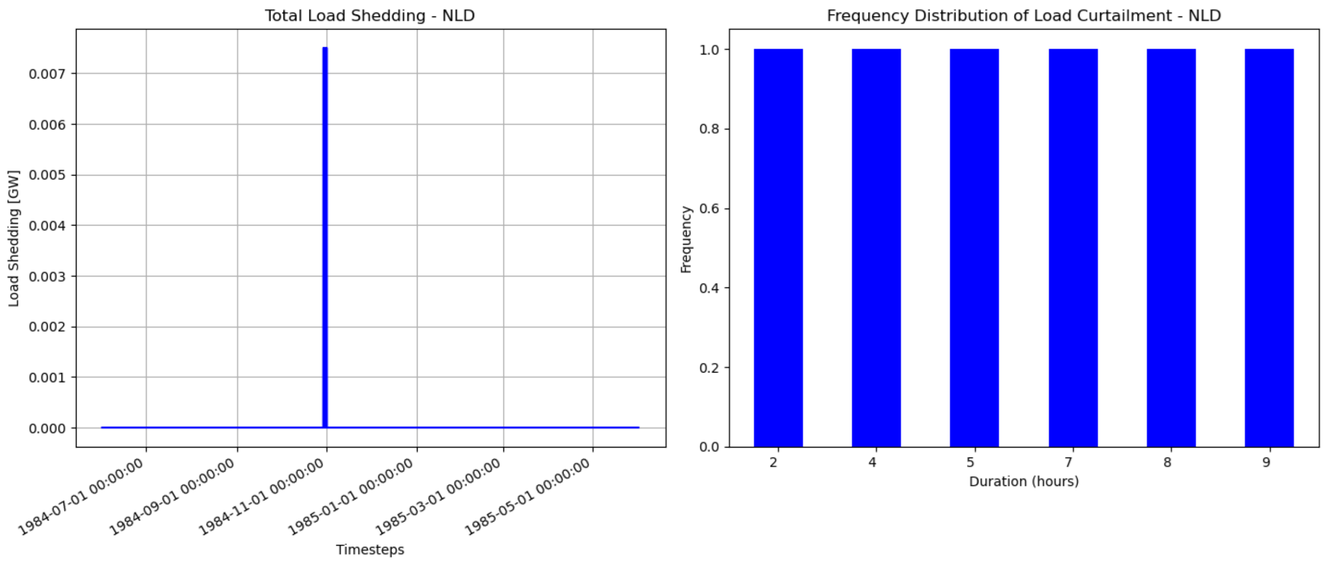


Figure 5.17: Load Shedding Distribution - Case of halved LDES energy capacity. The figure shows the reduction in EENS and LOLE reinforced by the complementary role of SDES and LDES. In particular, the participation of LDES seems to be related to a reduction in LOLE.

6
Discussion of the Results

In the previous chapter, the results obtained from the various simulations were presented. This chapter discusses how the finding can answer the research question: *What are the capacity value drivers of long-duration electricity storage for an interconnected European power system in 2050 in a context of high penetration of renewables and future climate?*. Section 6.1 will first analyze the background and scope of the project to provide context for the findings. Following this, Section 6.2 will focus on the main outcomes of the model and simulations. Section 6.3 will address the socio-economic implications of these results, exploring how the deployment of storage technologies could affect power system costs and energy security. Finally, the limitations of the research and potential areas for improvement will be discussed in Section 6.4.

6.1. Project background and scope

The problem that this thesis tries to solve is to assess to what extent long-duration electricity storage can contribute to the resource adequacy of a European interconnected system in 2050, in a context of uncertain and future climate. As climate concerns among governments are driving energy policies toward more sustainable electricity production with significant CO2 reductions, these long-term goals are being developed, tested and studied using advanced energy modeling tools, which predict a global increase in renewable energy production. This includes hydropower, biomass, geothermal, but most importantly, a substantial expansion of wind and solar power generation. However, solar and wind energy, known as variable renewable energy sources, present challenges for power sector management due to their variability across different timescales and their non-dispatchable nature, meaning operators cannot control their output beyond switching them off or reducing their output voluntarily. VRES significantly impact the power sector because they are prioritized in the merit order due to their zero marginal cost, necessitating that the remaining load is met by other dispatchable technologies.

The key challenge for power systems is to maintain reliability continuously through system planning and operation. Resource adequacy deals with the long-term planning of the power systems, as it involves the ability to meet long-term demand while considering supply-demand uncertainties. Due to the increasing share of VRES in the generation mix and the phase-out of traditional thermal generators, the weather will increasingly become a major factor in resource adequacy failures. Consequently, it is indispensable for energy planners to take into account meteorological uncertainty when doing resource adequacy assessments and recognizing the primary meteorological factors contributing to power system strain. However, future climate models present variability from one to the other and can represent a new source of uncertainty. For this reason, calibrating and adjusting historical climate data and scenarios to account for the likelihood calibrating and adjusting historical climate data and scenarios to account for the likelihood of climate change impacts can give useful information in assessing how past extremes can affect the power grid in the future. Moreover, to cope with an increasing reliance on weather-dependent renewables, flexibility options such as electricity storage, interconnection, and demand response will be needed to guarantee adequate future power systems.

LDES is becoming increasingly important for ensuring grid adequacy, especially as the penetration of variable renewable energy sources grows, necessitating different storage technologies for various discharge durations to optimize electricity costs. There is an ongoing debate around how much long-duration electricity storage is needed and what form it should take, particularly in comparison to other flexibility options like short-term storage or firm low-carbon energy sources, such as nuclear power. No prior study has thoroughly examined the benefits of LDES and the key factors driving its advantages in a future interconnected European power system. This research aimed to fill that gap by conducting energy assessments for an interconnected European grid in 2050, incorporating LDES under various scenarios. To achieve a more precise representation of future conditions, the analysis factored in weather variability and the effects of anthropogenic climate change.

6.2. Model and Simulations Findings

This section presents the results of the research, which was conducted in two main parts: first, the development of a capacity expansion model to determine the most cost-effective mix of generation, storage, and transmission investments; and second, a resource adequacy assessment of this system under various scenarios.

Capacity Expansion Results

The capacity expansion model simulated investments in generation and transmission capacity for a European interconnected system, based on assumptions about future electricity demand, technology costs, performance, and generator availability. This model was developed to endogenously determine the future levels of short-duration and long-duration energy storage (SDES and LDES), modeled as batteries and hydrogen respectively, that will be necessary for the future power system. Existing projections, such as those from the Ten-Year Network Development Plan, often focus on hydrogen needs for the entire energy system, not just the power sector. The model results show that as the share of variable and inflexible low-carbon electricity sources—such as solar, wind, and hydropower—exceeds 90%, conventional thermal generators are significantly reduced. In fact, VRE sources, such as wind and solar, fully utilize their maximum allowed capacity in the model's capacity expansion constraint, while other technologies like nuclear and gas power did not reach their full potential in all countries. Lithium-ion batteries, with the lowest installed capacity cost, made up the largest share at 61 GW, while hydrogen storage contributed 30 GW.

The expansion results were based on 10 years of weather data (from 1985 to 1995). Analysis of the top 10 netload events across different years revealed that each year contributed to at least one peak net load event, with each country experiencing peak demand hours in at least four distinct years. This highlights the importance of using multiple years of weather data when planning capacity expansions to ensure the system is resilient under varying conditions. Additionally, a seasonal analysis showed that the majority of peak net load hours occurred in winter and autumn. This provides valuable insight for energy planners, suggesting that long-duration energy storage systems should be strategically charged during the summer to be ready for discharge during the high-demand periods in winter and autumn.

Impact of LDES dispatch on resource adequacy

In Section 5.2, different approaches to modeling LDES dispatch were analyzed to highlight how varying model structures and initial assumptions can significantly affect the results. LDES must be dispatched in a way that ensures energy reserves are available during critical periods, conserving energy when demand is low and replenishing reserves throughout the year. Without a specific dispatch strategy, the typical economic dispatch tends to discharge LDES aggressively while delaying recharging, making it vulnerable to short-term outages and future system requirements. While this may be suitable for short-duration storage, where cost savings come with a slight reduction in reliability, it is unrealistic for systems relying on LDES or seasonal storage, which require longer planning horizons.

Three dispatch strategies for LDES were compared. In all cases, LDES was the last resource to be discharged, only used before resorting to load shedding. The first two strategies featured look-ahead periods of 72 hours and 200 hours, respectively, but neither had a dedicated charging strategy. The third strategy also used a 72-hour look-ahead period but introduced a charging incentive for both

SDES and LDES, prioritizing SDES for charging. The results indicated that proactive charging during lower-demand periods, such as the shoulder seasons, is important to ensure enough energy reserves for high-demand periods. Shorter look-ahead periods led to fewer full storage cycles due to shallow cycling and underutilization. This conclusion is supported by the fact that the 200-hour look-ahead strategy performed quite well, resulting in an EENS value only slightly larger than that of the third strategy, which included proactive charging. However, extending the look-ahead period too far becomes impractical, especially when modeling LDES or seasonal storage, which is likely to require operational procedures akin to those used in hydrothermal systems. [98].

Varying Discharge Duration and Comparison with SDES
In Section 5.4, resource adequacy assessments were performed to explore how variations in installed power and energy capacity of LDES and SDES impact reliability metrics such as EENS and LOLE.

The results demonstrate that increasing energy capacity is more effective at reducing EENS than adjusting installed power alone. Additionally, extending the discharge duration of LDES significantly mitigates long-duration load curtailment events. For instance, increasing the hydrogen discharge duration from 50 to 200 hours reduced EENS by 34% and LOLE by 42 %. This suggests that storage capacity value is closely tied to both power rating and energy storage capacity to adequately cover peak demand periods. Table 6.1 presents the frequency distribution of load shedding durations across different time ranges for all the cases analyzed in this study, highlighting a clear pattern: as the LDES discharge duration increases, LOLE decreases, and load curtailment events become shorter.

However, when comparing the EENS reduction achieved by increasing the E2P ratio of LDES with the reduction obtained by enhancing the energy capacity of SDES, as shown in Section 5.4, one notable observation emerges: increasing the E2P ratio of LDES does not reduce the peak magnitude of the main load curtailment event. Increasing the energy capacity of SDES could contribute to reducing the magnitude of these events and their duration, however, it may not be economically viable, as shown in Section 2.3.1. Furthermore, comparing the halved power case to the E2P = 200 hours case reveals a 63% reduction in EENS for the E2P = 200 hours case, though accompanied by a 10% increase in LOLE. This indicates that increasing the power capacity of SDES technologies is effective at mitigating the peaks of load curtailment events, thereby lowering EENS while increasing the discharge duration of LDES has more impact on the LOLE rather than the EENS.

To summarize, storage systems incorporating both battery and hydrogen storage offer greater reliability than one relying on a single energy storage solution. This approach leverages the strengths of each type: batteries provide quick response and are ideal for short-term energy needs, while hydrogen can cover longer durations. This diversification reduces the risk associated with relying on a single storage technology, particularly during periods of low renewable energy availability or high demand. However, power systems must optimally balance SDES and LDES to ensure adequacy during extreme weather events. This balance is challenging as the benefits of adding more SDES or more LDES have to be compared with the disadvantages. For example, increased SDES can lead to an increased electricity demand due to the electricity required to charge the batteries and potential grid congestion, while LDES can contribute to better VRES integration. Ultimately, these findings suggest that increasing the energy capacity of SDES has a more significant impact on reducing EENS, whereas increasing the discharge duration of LDES is crucial for achieving the greatest reduction in LOLE. This raises questions about which metric—EENS or LOLE—should be prioritized when evaluating power system adequacy.

Table 6.1: The frequency for certain ranges (in hours) of load shedding duration is presented. It can be noticed that increasing the discharge duration of LDES can effectively reduce the duration of load-shedding events while increasing the power capacity of SDES contributes to a lower EENS but a higher chance of having longer load curtailment events. A solution is either increasing the energy capacity of SDES, which may not be economically viable or increasing the discharge duration of LDES.

CASE	1-2	3-5	6-8	9-11	12-15	16-19
E2P = 50 hours	2	4	1	4	0	5
E2P = 100 hours	2	3	2	4	0	3
E2P = 200 hours	2	5	3	3	0	1
Halved Power Capacity	1	5	1	1	0	3
1/4th Energy Capacity	0	1	0	1	1	1
Halved Energy Capacity	1	2	2	1	0	0

6.3. Socio-Economic Impact

The findings discussed earlier in this paper raise important questions regarding which metric, EENS or LOLE, should take precedence when evaluating system adequacy and defining a reliability standard. As a matter of fact, according to Article 25 of Regulation 2019/943, Member States are required to have a reliability standard in place when implementing capacity mechanisms [99]. The purpose of this standard is to determine the capacity needed within the capacity mechanisms. These mechanisms have become a key regulatory tool in liberalized power systems undergoing decarbonization, ensuring that an adequate resource mix is available to meet the reliability targets set by regulators [99]. The standard is calculated using metrics like the Value of Lost Load (VOLL) and the Cost of New Entry (CONE) over a defined period and is expressed in terms of EENS and LOLE, which indicate the optimal level of security of supply [99]. This procedure is depicted in Figure 6.1, which illustrates how the optimal capacity volume is determined by maximizing the net social benefit of electricity. Social benefit is maximized when the marginal cost of capacity equals the marginal benefit. The marginal cost is primarily driven by the fixed costs of adding an MW of peaking capacity (CONE), while the marginal benefit reflects the value of outages avoided through additional capacity, quantified as VOLL multiplied by LOLE.

This research highlighted that today's reliability events are more diverse in size, frequency, duration, and timing. Understanding these variations is essential for selecting appropriate resource solutions. Mitigation strategies need to be tailored to address these different scenarios, as each resource type brings distinct capabilities, as seen when comparing LDES and SDES. For these reasons, grid planners and regulators must have a clear understanding of the costs associated with achieving different reliability targets, recognizing that each resource has specific strengths and limitations, which need to be optimally balanced for modern power system adequacy. In the future, both EENS and LOLE might need to be considered together for a comprehensive approach to modern power system adequacy.

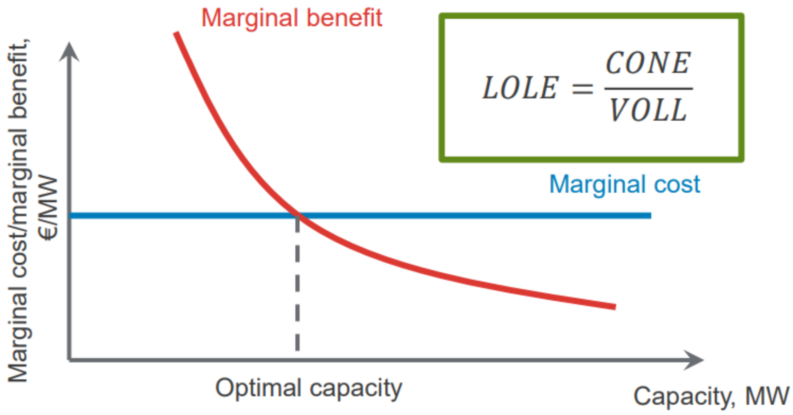


Figure 6.1: Economic equilibrium determining the reliability standard

The simulations revealed that the dispatch of LDES significantly impacts EENS, raising important economic considerations. To optimize dispatch, LDES should operate on an annual cycle, with the hydrogen system completing about 5 cycles per year. However, the uncertain cost competitiveness of LDES raises concerns about its widespread deployment. As storage duration increases and dispatch becomes more optimized, fewer operating cycles of LDES are expected each year, as discussed in Section 5.2. This necessitates finding incentives for storage operators to maintain adequate storage levels, even when it is used only a few times annually. Additionally, one of the main barriers to energy storage investment is the gap in EU legislation, which results in grid fees being applied both during charging and discharging [100]. This issue of double grid fees is a significant concern for investors in countries where both generation and consumption are taxed [100]. Moreover, the 2019 E-Directive prohibits storage ownership and operation to network operators, such as TSOs and DSOs, from owning storage facilities [100]. As a result, storage plant owners must compete in electricity markets, often with less access to critical information than SOs, such as wind and load forecasts or network and plant statuses [100].

To promote the construction of energy storage facilities, capacity payments or other non-market incentives are also essential to support storage investments. These incentives are particularly important because the societal benefits of energy storage, such as reduced production costs, lower GHG emissions, and grid stabilization, do not always generate market revenues for storage owners [101]. To bridge the current cost gap and address technological uncertainties in the emerging LDES market, governments and industry leaders must stimulate market development by fostering an investment-friendly ecosystem. Three critical areas for support are long-term system planning to generate investment signals, scaling up deployments to kick-start the market, and developing mechanisms to capture and monetize the value of LDES.

6.4. Limitations

It is essential to acknowledge the limitations of this research to better understand how the results might translate to real-world scenarios. Below, several of these limitations are outlined, along with potential areas for improvement.

The planning mode results were obtained using heuristic clustering of timesteps, chosen to reduce computational time. A 6-hour time resolution was used for most of the ten years of weather data considered. However, this may have introduced an end effect when modeling photovoltaics, as solar capacity factors can vary on shorter timescales. This lower resolution might lead to an overestimation of storage requirements. Exploring alternative time clustering techniques and comparing the results could offer insights into the system's actual storage needs.

The weather data used in this model was based on historical data calibrated with future climate projections, which carry inherent uncertainty. Incorporating multiple climate models to compare outcomes could enhance the robustness of the results. Additionally, the hydropower dataset relied on historical records due to the absence of future projections. Given the potential for climate change to cause droughts, integrating hydropower timeseries that account for this phenomenon would provide a more realistic evaluation of future power system stress.

A degree of uncertainty was introduced through the implementation of forced outage patterns. However, the results showed that resource adequacy was less sensitive to this factor, primarily due to the system's growing dependence on weather patterns. To test system reliability further, adding more uncertainty variables could be beneficial. For example, using more than one year of weather data for resource adequacy assessments, or introducing uncertainty into demand timeseries, could improve the analysis.

The dispatch strategy for LDES could also be optimized. Although the current approach performs well in managing reserves and charging when needed, it does not accurately reflect real-world electricity market dynamics. For instance, the current model assumes a negative charging cost, implying that storage operators earn revenue when charging, which isn't realistic. A more sophisticated approach could be the one discussed in [73], which involves introducing a variable for the value of stored energy. In this case, if the marginal price of energy falls below the value assigned to stored energy, the storage device would charge, while if the marginal price exceeds this value, the device would discharge.

Finally, while the assumptions and inputs for this study were carefully defined and drawn from credible sources, the long-term horizon to 2050 introduces considerable uncertainty. Therefore, the findings should be interpreted with caution, especially when considering long-term predictions.

7

Conclusion and Recommendations

The problem that this thesis tries to solve is to assess to what extent long-duration electricity storage can contribute to the resource adequacy of a European interconnected system in 2050, in a context of uncertain and future climate. LDES is becoming increasingly important for ensuring grid adequacy, especially as the penetration of variable renewable energy sources grows, necessitating different storage technologies for various discharge durations to optimize electricity costs. There is an ongoing debate around how much long-duration electricity storage is needed and what form it should take, particularly in comparison to other flexibility options like short-term storage or firm low-carbon energy sources, such as nuclear power. No prior study has thoroughly examined the benefits of LDES and the key factors driving its advantages in a future interconnected European power system. This research aimed to fill that gap by conducting energy assessments for an interconnected European grid in 2050, incorporating LDES under various scenarios. This objective is described by the research question: *What are the capacity value drivers of long-duration electricity storage for an interconnected European power system in 2050 in a context of high penetration of renewables and future climate?*. To achieve a more precise representation of future conditions, the analysis factored in weather variability and the effects of anthropogenic climate change.The goal was to obtain a deeper understanding on what can influence the ability of LDES to bring resource adequacy to the system. This chapter will provide the final conclusions of this project.

7.1. Conclusion

The core challenge for power systems is ensuring continuous reliability through careful planning and operation. Resource adequacy focuses on long-term planning, addressing the system's capacity to meet future demand while accounting for supply-demand uncertainties and it consists of transmission adequacy and generation adequacy. In contrast, system security handles the short-term reliability of the power supply. This research places particular focused on generation adequacy. Various metrics, including Expected Energy Not Supplied (EENS), Loss of Load Expectation (LOLE), and Loss of Load Probability (LOLP), can be calculated and compared against European benchmark values. This study quantified EENS and LOLE for a power system comprising eight European countries, with electricity demand projections adjusted to reflect those forecasted for 2050. The decision to focus on EENS and LOLE was driven by the fact that they capture two key dimensions of load curtailment: severity and duration.

A capacity expansion model was developed using the energy modeling framework Calliope. This model incorporated ten years of weather data, employing calibrated historical data and climate projections to assess how past extreme weather events might influence future grid performance, ultimately helping to design a more resilient system. The capacity expansion model simulated investments in generation and transmission capacity across the interconnected system and endogenously determined the future levels of both short-duration and long-duration energy storage (SDES and LDES). the study analyzed seasonal patterns in peak net load, defined as total demand minus total variable renewable energy (VRES) generation. The results showed that the highest risks to system stability occurred during peak demand periods in autumn and winter, suggesting that summer could be an optimal time to schedule generator maintenance and charge LDES. The study analyzed seasonal patterns in peak net load, defined as total demand minus total variable renewable energy (VRES) generation. The results showed that the highest risks to system stability occurred during peak demand periods in autumn and winter, suggesting that summer could be an optimal time to schedule generator maintenance and charge LDES.

After establishing the installed capacity for VRES, thermal generators, and storage, a Monte Carlo resource adequacy assessment was performed. The chosen period, spanning from June 1, 1984, to June 1, 1985, included a particularly severe winter in 1985, marked by extreme weather that heavily impacted energy supply and demand. This scenario provided insights into the role of long-duration storage during system stress. Forced outage patterns for thermal generators were incorporated, however, the resource adequacy results showed a low sensitivity to these patterns, due to the large dependence of the grid on VRES. Multiple tranches of load curtailment were modeled with increasing marginal costs. The capacity for each tranche was distributed proportionally across countries, creating a strategy that minimized load shedding and maintained a unique LOLE value. An analysis of imports and exports during periods of load curtailment revealed that transmission capacity was never fully utilized during these events. This suggests that increasing transmission capacity alone would not resolve the issue of load curtailment.

By simulating different LDES dispatch strategies, it became evident that the operational profile of LDES plays a critical role in the system's resource adequacy. The operational profile of LDES is characterized by fewer cycles, strategic dispatch aimed at minimizing EENS, and a strong dependence on the value attributed to stored energy. Optimal dispatch strategies aim to limit discharging to periods of potential energy shortages while encouraging strategic charging. LDES technologies, such as hydrogen storage, tend to cycle more frequently when the stored energy lacks a defined monetary value, often resulting in shallower cycles and underutilization. Such frequent cycling can deplete storage reserves prematurely, leading to suboptimal performance during high-demand periods. The results also showed that extending the look-ahead period beyond the expected storage duration could improve performance, though this approach is often impractical for LDES. In scenarios with controlled charging and discharging, LDES was dispatched more conservatively, functioning as a buffer during peak demand and cycling less frequently. This resulted in enhanced supply security and lower EENS. Additionally, the number of cycles that LDES undergoes annually is influenced by the energy-to-power (E2P) ratio. As the E2P ratio increases, the frequency of cycles decreases. Consequently, policy and market design play a crucial role in shaping the operational profile of LDES. Current policies supporting LDES need to be strengthened, and market mechanisms should be designed to provide adequate financial returns to encourage investment.

Varying the E2P ratio of LDES allowed to understand that the duration of energy storage significantly affects both EENS and LOLE. A higher E2P ratio and increased storage capacity are key to effectively reducing EENS. While power capacity is typically the focus in resource adequacy assessments, the value of storage is closely tied to both its power rating and energy storage capacity to meet peak demand. Storage systems with higher E2P ratios are more capable of sustaining energy output during periods of low renewable generation or high demand, making them more effective at reducing EENS. This is especially critical during extended periods of low renewable energy output, such as prolonged cloudy or windless days. For example, increasing the storage duration from 50 to 200 hours reduced EENS by 34% and LOLE by 42%. However, beyond a certain E2P threshold, improvements in EENS tend to plateau.

The simulations also showed that LDES and SDES serve complementary roles in reducing EENS. SDES technologies are particularly effective in addressing short-term disruptions, such as fluctuations in wind power output. While increasing the E2P ratio of LDES does not significantly reduce the peak magnitude of the largest load curtailment events, increasing the power capacity of SDES can help mitigate the magnitude and duration of these events, though it may not always be economically viable due to the higher energy investment costs. The lower power investment costs of SDES could be exploited to lower EENS, however, LDES plays a more substantial role in reducing LOLE. This research highlighted the increasing diversity of reliability events in terms of size, frequency, duration, and timing. Understanding these variations is essential for selecting appropriate resource solutions. Grid planners and regulators must carefully consider the costs associated with achieving different reliability targets, balancing the strengths and limitations of each resource type to ensure modern power system adequacy.

7.2. Answer to Research Question

When projecting 1985, which presented several episodes of cold snap and wind drought, into the future the resource adequacy assessment conducted showed that power systems with a high penetration of renewables need large amounts of storage. LDES significantly contributes to the resource adequacy of a power system by providing a reliable source of backup power. This ensures that there is sufficient generation capacity available to meet peak demand, even during periods of low renewable generation. In this context,LDES helps maintain adequate generation capacity to meet peak demand, thus displacing the need for firm generation capacity. This research demonstrated that the value drivers of storage depends not only on the power rating of the storage but also on the energy storage capacity and the discharge duration as it has to cover the duration of the peak demand. In addition to that LDES capacity value depends also on the way this technology is dispatched. Effective dispatch optimization minimizes EENS by ensuring that stored energy is utilized when it is most needed. The document shows that optimal dispatch strategies significantly reduce EENS, emphasizing the importance of smart energy management to maximize the value of LDES. However, while LDES can reduce LOLE by covering long-term energy shortages, it may not always mitigate the magnitude of peak load curtailment events.

Finally, the combination of both storage types leads to greater reductions in EENS compared to either type alone. The study showed that the best storage technologies to balance the system depend on the duration of deficit events it is designed to mitigate. Therefore, the integration of LDES with SDES enhances overall capacity value by providing a comprehensive storage solution that addresses both short-term and long-term energy needs. SDES can handle rapid, short-duration fluctuations, while LDES covers extended periods of energy deficit. This underlines the necessity of integrating various storage solutions.

A
Appendix

A.1. Impact of LDES Discharge Duration on RA - Load Sheddig Distribution

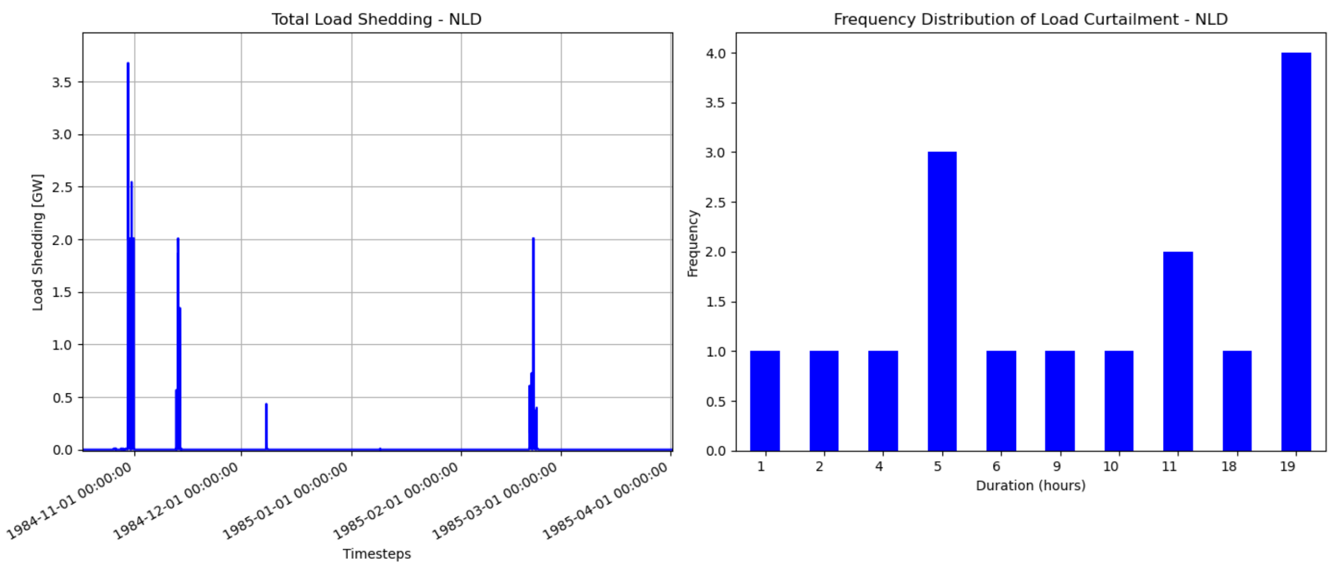


Figure A.1: Load shedding and load shedding frequency distribution for an E2P ratio of 50 hours.

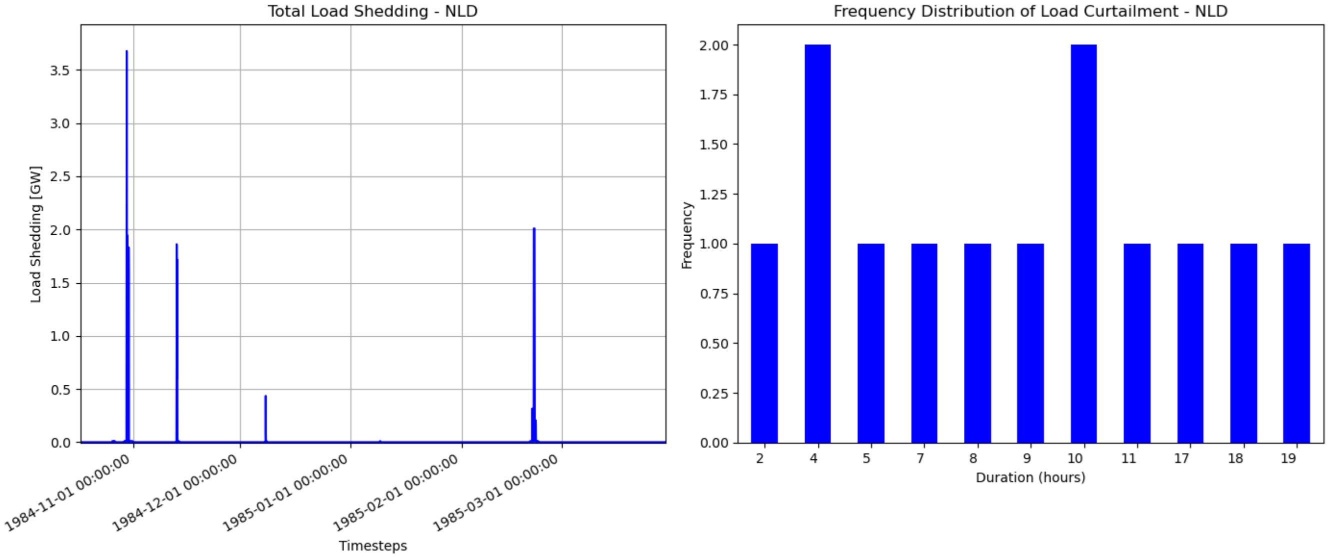


Figure A.2: Load shedding and load shedding frequency distribution for an E2P ratio of 100 hours.

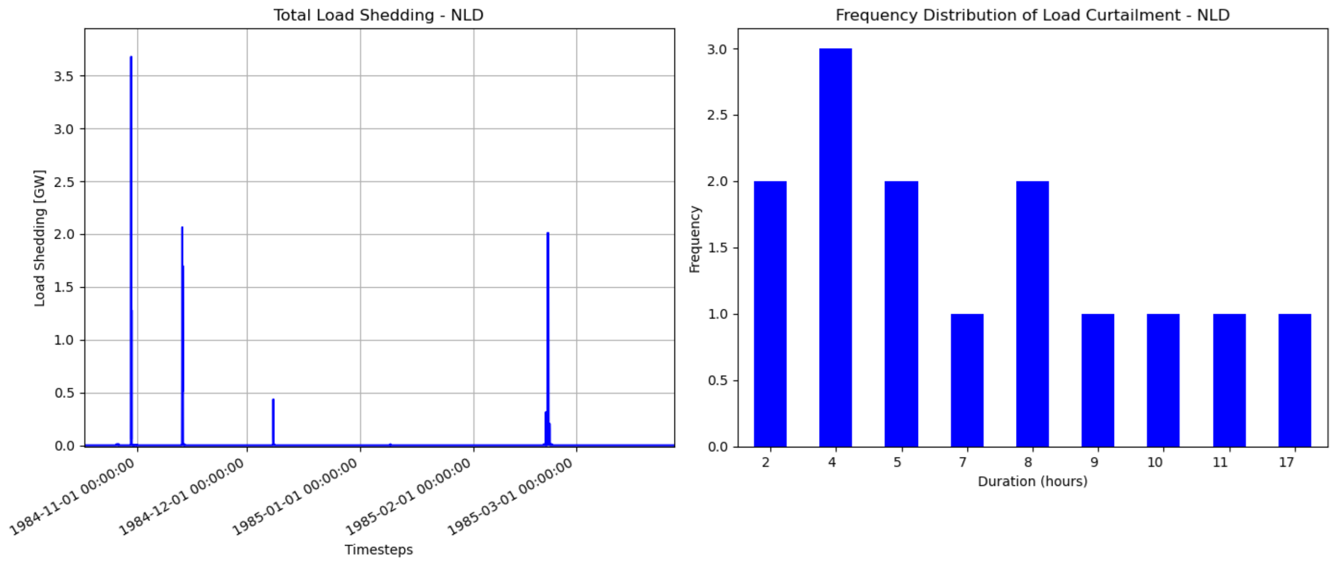


Figure A.3: Load shedding and load shedding frequency distribution for an E2P ratio of 200 hours.

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