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# Modeling the Role of Battery Storage in the Nordic Energy System

## A 10-Year Perspective on Renewable Integration and Capacity Expansion

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**Abstract**

The transition to a sustainable energy system is a pressing global challenge, and battery energy storage system (BESS) are emerging as a promising solution to improve renewable energy integration and grid stability. This thesis examines the integration of BESS into the Nordic energy system between 2023 and 2033, focusing on their role in improving renewable energy adoption and grid performance. The study aims to evaluate the potential of BESS investments in addressing variability in renewable generation and optimizing system costs. Utilizing the EMPIRE model, a cost-based energy system optimization tool, the study evaluates investments in BESS and renewable capacities to explore their impact on overall system costs. The analysis reveals a highly uneven adoption of BESS throughout the region, with Sweden leading because of its diverse mix of renewable energy. In contrast, other countries such as Norway, Finland, and Denmark rely on alternative flexible solutions such as hydro storage, gas technologies, and existing interconnections. The results highlight the complex interplay between storage, renewable resources, and existing infrastructure, emphasizing that the path to a sustainable energy system is shaped by unique national circumstances. Although BESS is shown to be effective in mitigating renewable curtailment and supporting grid reliability, its limited adoption in certain countries suggests that broader strategies are equally crucial. The study acknowledges limitations, such as static assumptions for renewable generation and demand, which provide opportunities for further research to refine energy models and explore complementary flexibility options. While the work primarily provides a case study of BESS integration in the Nordic region, it offers a starting point for assessing storage technologies within diverse energy contexts.

**Keywords** Battery Energy Storage System, Renewable Energy Integration, Nordic Energy System, Capacity Expansion Models, Battery Market Development, EMPIRE Model

# Contents

# Symbols and Abbreviations

## Symbols

| | |
|---|---|
| $CO_2$ | carbon dioxide |
| $tCO_2$ | tonne of $CO_2$ |
| $MtCO_2eq$ | megatonnes of $CO_2$-equivalent |
| kg $CO_2$/GJ | kilograms of $CO_2$ per gigajoule |
| €/$tCO_2$ | euros per tonne of $CO_2$ |
| MW | megawatts |
| MWh | megawatt-hours |
| GWh | gigawatt-hours |
| MW/MWh | power-to-energy ratio |
| €/kW | euros per kilowatt |
| €/MW | euros per megawatt |
| €/MWh | euros per megawatt-hour |
| €/GJ | euros per gigajoule |
| €/MW-km | euros per megawatt-kilometer |
| km | kilometers |

## Abbreviations

| | |
|---|---|
| BESS | battery energy storage system |
| CCGT | combined cycle gas turbine |
| CCS | carbon capture and storage |
| CEMs | capacity expansion models |
| DIMENSION | Dispatch and Investment Model for European Electricity Markets |
| DIME | Dispatch and Investment Model for Electricity Markets in Europe |
| DSM | Demand Side Management |
| E2M2 | European Electricity Market Model |
| EMPIRE | European Model for Power system Investment with Renewable Energy |
| HVAC | high-voltage alternating current |
| HVDC | high-voltage direct current |
| IEA | International Energy Agency |
| MESSAGE | Model for Energy Supply Strategy Alternatives and their General Environmental Impact |
| NEA | Nuclear Energy Agency |
| NREAP | National Renewable Energy Action Plan |
| OCGT | open cycle gas turbine |
| TIMES | The Integrated MARKAL-EFOM System |
| VRE | variable renewable energy |
| WCSS | Within-Cluster Sum of Squares |

# 1 Introduction

Due to the concerning and growing consequences of climate change, there has been a worldwide shift towards the usage of renewable energy sources. Recent years have been the warmest on record, with global average temperatures rising 1.1°C above pre-industrial levels by 2019 [1]. The consequences, consisting of extreme weather events, underscore the urgent need for sustained action to safeguard global well-being [1].

The European Union (EU) has established itself as a leader in response to this struggle. The European Green Deal aims to achieve climate neutrality for the EU by 2050 [1]. The interim objective is to reduce greenhouse gas emissions by 55% by 2030 in comparison to 1990 levels [1]. In accordance with this ambitious goal, the Nordic countries have established their own rigorous climate objectives. Finland targets climate neutrality by 2035, Denmark targets a 70% reduction in emissions by 2030, Norway aims for a 55% reduction by 2030, and Sweden plans a 63% reduction by 2030, with climate neutrality by 2045 [2].

Battery energy storage system (BESS) has become essential for incorporating renewable energy into power systems, aiding in grid stabilization by holding energy during peak output and releasing it when demand surpasses supply [3]. Recent improvements in lithium-based batteries, recognized for their high energy density and extended longevity, are crucial for large-scale applications such as electric vehicles and renewable energy storage [3].

However, the growth of the BESS market in the Nordic region has been uneven. Sweden and Finland have led in deploying grid-scale battery systems, with Sweden expecting over 400 MW for operation in 2024 and Finland anticipating over 300 MW of grid-scale batteries in the next two years [4]. Meanwhile, Norway, despite its ambitions to lead the battery storage market, has focused on hydro resources for long-duration storage, falling behind in BESS deployments [4]. In Sweden, where the demand for flexibility services may soon outpace the pace of battery installations, this rapid development has raised concerns about potential market saturation [4].

Given the rapid expansion of BESS and the potential risks of overcapacity, capacity expansion models are essential for optimizing the planning of generation, storage, and transmission infrastructure. These models aim to minimize total system costs over long-term horizons, ensuring that investments in technologies such as BESS align with renewable energy targets while considering system constraints [5].

In this context, a variety of models have been developed to assist in long-term energy system planning. For example, TIMES [6] and MESSAGE [7] focus on minimizing long-term costs but face challenges in representing short-term constraints. Different models, such as DIMENSION and E2M2, are better at short-term dispatch and market interactions, but they are not as good at cross-sectoral integration or stochastic analysis [8]. As renewable energy and storage technologies become more prevalent, these models need to evolve to balance long-term planning with the uncertainties of short-term decisions.

Despite these developments, these models frequently abstract away complexities because they are simplified depictions of the real world. This could lead to different results depending on the modeling method used, especially in systems that are saturated with variable renewable energy (VRE) [5]. This abstraction may result in deficiencies when modeling specific technologies such as BESS, which necessitate a thorough examination of their operational dynamics and market relations.

The EMPIRE model (European Model for Power System Investment with Renewable Energy) [9] helps address some of the limitations seen in other capacity expansion models by combining long-term investment planning with short-term operational strategies, particularly under high renewable energy penetration scenarios. While it does not fully resolve all challenges, EMPIRE provides a more detailed framework for modeling the interactions between renewable energy variability and energy storage technologies. The aim of this thesis is to adapt the EMPIRE model to estimate the development of the battery market in the Nordics between 2023 and 2033, with five investment periods occurring every two years. This time frame was selected because rapid growth is expected within the battery market, with possible saturation within the next decade [4]. By adopting the EMPIRE model, this research aims to provide insights into the role of battery storage in the Nordic energy landscape, focusing on how investment and operational decisions may evolve.

This thesis is structured as follows: Chapter 2 reviews existing capacity expansion models and their purpose, Chapter 3 details the EMPIRE model, Chapter 4 outlines the methodology for adapting the model for the Nordic region, Chapter 5 discusses the results from the analysis of the Nordic dataset, and Chapter 6 summarises the findings.

# 2 Literature review

This literature review will explore modeling approaches used to evaluate long-term energy system investments, with a specific focus on the integration of BESS. To understand how BESS can support the transition to renewable energy in the Nordic region, the review will first introduce capacity expansion models and explain their importance in long-term strategic planning. The discussion will then differentiate between top-down and bottom-up models, emphasizing the relevance of long-term bottom-up models for this study. Key models in this sector will be reviewed to highlight their strengths and limitations. This review will identify gaps in these existing models, demonstrating the need to adapt the EMPIRE model to better capture the role of BESS in the Nordic energy system.

## 2.1 Capacity Expansion Models

Capacity expansion models, or CEMs, are essential tools used to plan and optimize energy systems over long periods. These models assist decision-makers in determining the most cost-effective approach to constructing and expanding energy infrastructure, encompassing generation, storage, and transmission systems [10]. CEMs are crucial for understanding how current decisions will impact future energy systems, often projecting decades ahead [10].

Policymakers and energy planners rely on CEMs to simulate different scenarios and strategies, taking into account factors such as fluctuating fuel prices, changes in technology, and evolving energy policies [10]. Through these simulations, CEMs help identify the optimal mix of energy resources and offer insights into how power systems can evolve over time [11].

The classification of CEMs has evolved over time. [12] laid the groundwork by differentiating models based on factors such as top-down versus bottom-up approaches, as well as their focus on either short- or long-term planning horizons [13]. This framework was enhanced by adding more details about the model's purpose, its mathematical structure, its focus on geography, and its sectoral coverage [13, 14]. Later, the conversation shifted toward hybrid models, blending both bottom-up and top-down approaches [13, 15]. Further refinements were made in 2013, introducing a more balanced classification system that gave equal weight to all the key characteristics identified earlier [13, 16]. [13, 17] present a thorough review of 13 tools that focused on community-scale energy systems. The review looked at data input types, the supply technologies, and the demand-side management and storage methods [13, 17]. These ongoing efforts to refine CEM classifications underscore the increasing complexity of energy systems and the need for models that can address both technological innovations and policy challenges.

CEMs can be broadly classified into two types based on their analytical approach: top-down and bottom-up models [13, 18]. Top-down models analyze the relationship between the energy sector and the broader economy. This allows for the assessment of the socio-economic impacts of energy and climate policies, including effects on employment, public welfare, and economic growth [13]. These models provide a macroeconomic perspective, focusing on how changes in the energy system influence the overall economy rather than specific technological components [13]. However, this often limits their ability to assess sector-specific or technology-specific policies, making them less effective for analyzing energy technology choices [18].

In contrast, bottom-up models offer a more detailed and technology-oriented analysis of energy systems. These models focus on individual technologies and how they interact across various energy sectors, making them suitable for evaluating the integration of renewable energy sources and energy storage systems [13, 18]. While bottom-up models are valuable at providing insights into the technical and economic performance of energy technologies, they may not fully capture broader economic impacts, such as employment or gross domestic product changes, which are more typically addressed by top-down models [18].

Within bottom-up models, a further distinction can be made between short-term and long-term models [13]. Short-term bottom-up models prioritize operational aspects, such as real-time electricity dispatch and balancing supply and demand on an hourly or daily basis [13]. This helps in addressing immediate challenges such as grid stability and flexibility [13]. In contrast, long-term bottom-up models are better suited for strategic planning and evaluating decisions on infrastructure investments such as generation, storage, and transmission over extended time horizons [13]. Given the focus of this thesis on integrating BESS into the Nordic energy system, a long-term bottom-up model is a better choice for understanding how BESS investments will aid renewable energy integration and impact the system over time.

## 2.2 Long-Term Bottom-Up Models

Long-term bottom-up models are used to project the evolution of energy systems over extended periods. These models focus on capacity expansion planning, particularly through infrastructure investments, which is important for meeting future energy demands. By identifying optimal investment strategies, these models ensure long-term reliability and sustainability. Their emphasis on infrastructure development provides key insights for transitioning to low-carbon energy sources.

In contrast to short-term models that emphasize market dynamics or immediate technology adoption, long-term bottom-up models offer an enhanced perspective on strategic planning, particularly in evaluating the infrastructure required to integrate VRE sources. Their strength lies in addressing large-scale challenges, making them well-suited to analyze the Nordic energy system's transformation.

The following sections will review prominent long-term bottom-up models, examining their structure and potential for analyzing renewable energy integration.

### 2.2.1 TIMES

The TIMES (The Integrated MARKAL-EFOM System) [6] model is a flexible, bottom-up, optimization-based model designed to represent energy system dynamics over a multi-period time horizon. The MARKAL (MARKet ALlocation) and EFOM (Energy Flow Optimization Model) models served as inspiration for TIMES, which simulates the ideal configuration of generation, storage, reserve capacity, and transmission infrastructure at the lowest total system cost. Its scope encompasses decisions around equipment investment, operation, energy trade, and fuel sourcing while meeting criteria such as emissions limits or policy goals. The model includes mechanisms to manage reserve capacity. One such mechanism is the peaking reserve constraint, which ensures sufficient production capacity to meet peak demand with a user-defined margin. This accounts for uncertainties such as equipment failures or demand surges. Technologies are assigned specific coefficients to determine their contribution to peak capacity. Reliable power plants can contribute fully, while variable technologies may have reduced contributions. This approach ensures that the model can balance short-term supply and demand while maintaining system reliability. [6]

The model also models the interactions between energy producers and consumers, seeking to establish supply-demand equilibrium. Market imperfections such as taxes, subsidies, and constraints can be incorporated to simulate policy interventions (such as emissions regulations), which makes the model highly adaptable to different regulatory contexts. [6]

The model operates on a flexible time structure, divided into user-defined periods spanning several years, allowing it to simulate long-term developments in the energy system. It separates data inputs from the time horizon, enabling users to adjust time frames without extensive recalibration, thus simplifying the assessment of long-term trends and scenarios. One of TIMES' strengths lies in its use of time slices, where each year is subdivided into smaller units, such as seasons, weekdays, and portions of the day. This aspect of the model is valuable for handling technologies sensitive to temporal variations, such as wind turbines or electricity storage. By modeling sub-annual time slices, the model can balance supply and demand in short-term intervals and ensure that peak loads are met. Technologies such as pumped storage or night storage devices are optimized to shift energy across time slices, which ensures that reserve capacity is available during peak demand periods. [6]

TIMES has been applied extensively in various regional and national contexts. The TIMES-Norway model was used to investigate hydrogen's role in decarbonizing an energy system transitioning from petroleum [19]. This study explored different levels of hydrogen production and consumption, assessing their impacts on system costs, emissions, and interactions with other energy sources [19]. In another application, VEDA-TIMES was used to model Indonesia's path to a 100% renewable energy system by 2050 [20]. This variant utilized an hourly resolution to analyze the role of energy storage in managing the variability of renewable sources such as wind and solar [20]. Furthermore, the MIRET-EU variant of the TIMES model was employed to assess hydrogen's contribution to achieving net-zero emissions in Europe by 2050 [21]. This study generated projections of hydrogen production, consumption, and imports across various sectors, examining policy scenarios and technology options [21].

### 2.2.2 MESSAGE

The Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE) [7], developed by the International Institute for Applied Systems

Analysis (IIASA), is a dynamic linear programming model that minimizes total energy supply costs over a specific time horizon. It finds the best balance between secondary energy needs (such as heating and electricity) and primary energy supplies (such as fossil fuels and renewables), taking into account things such as the availability of resources, the effects on the environment, and the rate at which new technologies are adopted [7].

MESSAGE uses a cost-minimization objective function to guide energy infrastructure investment decisions. It optimizes the addition of generation capacity under various resource and technological constraints, ensuring that investment strategies meet energy demand at the lowest possible cost [7]. These investment decisions are distributed across a dynamic time horizon, enabling long-term energy planning [7].

In addition to its cost-effectiveness, MESSAGE is flexible and adaptable, making it suitable for various regional contexts and global scenarios. The model incorporates load regions and distinguishes between domestic and imported resources, allowing it to optimize energy systems at national and international scales [7]. It also accounts for environmental constraints by simulating emissions of greenhouse gases and pollutants such as sulfur dioxide ($SO_2$) and nitrogen oxides ($NO_x$), making it a valuable tool for evaluating environmental policies alongside economic objectives [8].

MESSAGE also accounts for resource availability and depletion over time, influencing the shift in investment toward alternative technologies as costs rise with scarcity [7]. It considers the life cycle of infrastructure and imposes build-up constraints, preventing rapid, unrealistic technology deployment and reflecting the real-world challenges of scaling energy infrastructure [7].

The model's time horizon, divided into periods typically spanning 5 to 10 years, allows for long-term simulations of up to 120 years. This design allows MESSAGE to simulate gradual technological advancements, changes in resource availability, and environmental impacts over time. As a result, it is highly effective for strategic energy planning, including generation, storage, and transportation systems [7].

MESSAGE has been extensively used to support the development of global energy transition pathways such as those for the World Energy Council [22]. It has also played a key role in generating greenhouse gas emission scenarios for the Intergovernmental Panel on Climate Change [23]. Applications of MESSAGE include a wide range of studies, such as scenario assessments aimed at climate stabilization [24, 25], evaluations of innovation programs in the Iranian electricity sector [26], and the assessment of policy options for enhancing renewable energy adoption [27]. Additionally, the model has been used to analyze energy supply strategies in the Baltic states and to develop sustainable energy plans for Cuba [28, 29].

### 2.2.3 E2M2

The European Electricity Market Model (E2M2) [30], developed by the Institute of Energy Economics and Rational Energy Use (IER) at the University of Stuttgart, is a tool for optimizing and simulating electricity markets, with a particular focus on Europe. It operates under the assumption of a perfectly competitive market, where firms are price takers, and all participants have full access to information [31].

Under these conditions, E2M2 simultaneously optimizes long-term investment in new generation capacity and short-term unit commitment (scheduling and dispatching power generation to meet demand at minimum system cost) decisions [30]. The model also incorporates representations of thermal power plants and renewable energy sources. It includes flexibility solutions such as demand side management (DSM), energy storage systems, and power-to-heat technologies [30].

The primary objective of E2M2 is to minimize the system's total cost while meeting electricity demand. These costs include investments in new power plants, operational and maintenance costs, fuel costs, and carbon dioxide ($CO_2$) certificate costs [30]. Fixed costs of existing capacities are treated as sunk. However, the model captures the operating costs of both new and existing plants, including start-up costs that depend on the unit's minimum load during start-up [30]. This cost structure ensures the model accurately reflects the real operational conditions of power plants.

E2M2 uses important factors such as demand for electricity and heat, generation capacities, techno-economic parameters, and regulatory factors such as fuel prices and $CO_2$ emission limits as inputs [30]. It calculates marginal electricity prices using the dual variable of the power balance equation [30]. This provides insights into day-ahead market prices. It also estimates $CO_2$ certificate prices when emissions limits are imposed [32].

Key restrictions, such as system adequacy, govern E2M2. It ensures that electricity and heat demand are met while maintaining sufficient reserve capacity. The reserve requirement accounts for potential plant outages and the variability of renewable generation [32]. Technical constraints on thermal plants, such as ramping rates and minimum operating times, are incorporated using a mixed-integer linear programming approach. This allows for more precise unit commitment decisions [32]. The model also accounts for district heating systems, particularly combined heat and power (CHP) plants, which provide both electricity and heat [32].

E2M2 handles uncertainties in renewable energy generation using a stochastic framework. For example, it models wind power variability with a scenario recombining tree that simulates different wind conditions over time [32]. This approach allows for more resilient planning compared to deterministic models that assume perfect foresight.

The E2M2 model has been effectively applied to analyze and optimize electricity markets in various contexts. One notable application is its use in modeling the German electricity market [32]. In this context, the model simulates unit commitment and investment decisions while considering factors specific to Germany, such as district heating systems and net electricity exchange with neighboring countries [32]. Additionally, the model has been employed in a coupled modeling framework to identify and quantify the "efficiency gap" in electricity systems [30]. The "efficiency gap" here refers to the difference between the actual performance of electricity systems and their theoretically optimal performance under ideal conditions. Researchers achieved a more realistic picture of how well the system works and the associated costs by combining E2M2 with the agent-based market model for the investigation of renewable and integrated energy systems (AMIRIS) [33]. This model simulates the decisions that individual market actors make. This approach was chosen to account for deviations from perfect competition and market distortions [30].

### 2.2.4 DIMENSION

The Institute of Energy Economics at the University of Cologne (EWI) created the DIMENSION [34] model, a linear optimization tool meant to simulate the future development of European electricity markets, particularly under increasing integration of renewable energy sources. It aims to provide decision-makers with insights into the complex dynamics of power generation and system expansion in a market that must adapt to both conventional and renewable technologies. [34]

The model's optimization approach minimizes the total costs of the electricity system. These costs include variable costs, investment costs, maintenance expenses, and costs related to ramping power plants. It achieves this cost minimization while balancing electricity demand and supply within the system and simulating capacity constraints of both generation and transmission infrastructure. The model allows for investments in new generation capacity and evaluates storage technologies that can mitigate the variability of renewable energy sources. Additionally, it incorporates CHP plants by reflecting their technical features, such as their power-to-heat ratio, and simulates their role in the future energy mix. [34]

The model represents the electricity system using a graph structure where nodes represent different system components such as power plants, demand regions, and storage facilities. The connections between these nodes simulate the flow of electricity, enabling DIMENSION to evaluate how constraints such as transmission line capacities affect overall system performance. This structure is beneficial in providing a proper structure for simulating the operation of the electricity system under various constraints and future scenarios. [34]

A distinct feature of the model is its simulation of DSM and the role of electric vehicles (EVs) as virtual power storage, where EVs are modeled as flexible resources that can be charged when electricity demand is low and discharged when demand is high. By simulating these flexibility options, DIMENSION provides valuable insights into how future electricity systems could integrate new technologies while managing the increasing share of renewable energy. [34]

A limitation of the model is its exogenous treatment of renewable energy, requiring users to manually input the share and mix of renewable sources rather than allowing the model to optimize these values. The developers recognize that enabling the model to make these decisions would result in more accurate and insightful simulations. [34]

The DIME [35] model, a precursor to DIMENSION, has been applied in various research and consulting projects. DIME was used in energy policy analysis for the German government to evaluate scenarios for achieving climate targets [36, 37]. It also informed studies on integrating renewable energy for the German Energy Agency [38, 39] and assessed the impact of renewable deployment on conventional power markets [40]. Although these applications refer to DIME, they remain relevant for understanding the broader capabilities that DIMENSION inherits.

Despite their diverse applications, these models share inherent limitations in addressing the complexities of modern energy systems. TIMES and MESSAGE are powerful for long-term energy planning, but they only allow study of broad strategic goals and lack precise operational insights needed to comprehend short-term variations and technology-specific dynamics. DIMENSION and E2M2 both focus on long-term power system investment decisions and lack short-term operational flexibility, especially in high-renewable scenarios. Both models struggle to reflect the changing interactions between renewable energy sources and storage systems across temporal scales. These limitations place restrictions on modern energy systems that involve extensive modeling of renewable integration and operational flexibility.

To address these limitations, we have selected EMPIRE, which enables both long-term strategic planning and the short-term operational flexibility needed to analyze interactions between renewables and storage systems across temporal scales.

# 3 EMPIRE Model

The EMPIRE model [41] is a linear optimization model developed to optimize both investments and operations in power systems over a long planning horizon. Implemented as an open-source package, it includes a scenario generation procedure that allows users to explore various energy futures and analyze investment strategies under uncertain conditions. A core feature of EMPIRE is its formulation as a multi-horizon stochastic program, which handles uncertainty in VRE sources [41]. By generating different scenarios for renewable generation and electricity demand, the model allows users to evaluate a range of investment strategies [41]. This enables decision-makers to account for short-term operational needs alongside long-term strategic goals in an energy system shaped by fluctuating renewable supply and demand.

Figure 1 provides an overview of the EMPIRE model structure. It shows the model's key components: inputs, the multi-horizon stochastic optimization model, and outputs. The maps below the model structure illustrate possible transmission expansions and generation mixes across different regions, reflecting spatial optimization outcomes.

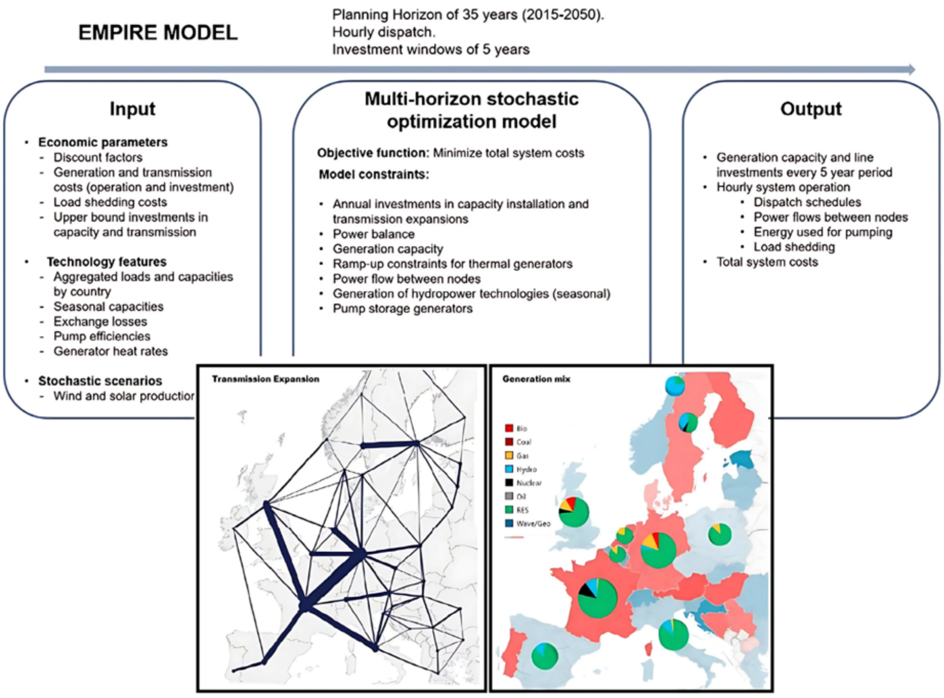


**Figure 1:** Overview of the EMPIRE model[9].

The subsequent sections will explore the components of the EMPIRE model in detail. Section 3.1 describes how the model handles uncertainty through its multi-horizon stochastic scenario structure. Section 3.2 follows by detailing how the optimization model minimizes both investment and operational costs while accounting for system constraints and uncertainties. Afterward, Section 3.4 provides an overview of the data required to simulate the system, covering the economic, technical, and stochastic inputs. These inputs feed into the model's decision-making process, leading to Section 3.5, which outlines the key results generated. Finally, Section 3.6 concludes with a comparison of EMPIRE with the other reviewed models.

## 3.1 Scenario Structure

The EMPIRE model is formulated as a multi-horizon stochastic program to handle uncertainty in the energy system. This approach integrates investment decisions with operational decisions across various operational scenarios, allowing the model to manage the interactions between strategic planning and the variability of renewable energy sources.

In EMPIRE, strategic decisions are made under the assumption of perfect foresight, meaning that the model assumes full knowledge of future variables such as fuel prices, technology costs, and demand growth when making long-term investments. Additionally, it is assumed that operational decisions within each period do not affect future strategic or operational decisions.[41]

Figure 2 illustrates the structure of a multi-horizon stochastic program that integrates both strategic and operational uncertainties. Each decision node represents a branching point where long-term strategic choices are made, which influence subsequent operational decisions. As one advances through various stages, uncertainties arise, leading to multiple potential future scenarios. This framework illustrates the complexity of decision-making across various horizons, where earlier strategic choices can limit or enhance future operational actions.

EMPIRE operates across two types of scenarios: investment scenarios and operational scenarios. Investment scenarios focus on long-term planning. Uncertainties such as technological advancements, regulatory changes, or market conditions could influence future strategies. Operational scenarios focus on short-term variations in load profiles and generation from wind, solar, and seasonal hydroelectric sources. Each investment period is evaluated against a set of operational scenarios, ensuring long-term strategies account for potential short-term conditions. [41]

To reduce computational complexity, EMPIRE employs temporal aggregation. Investment decisions are grouped into broader time blocks, minimizing the number of decision points required for long-term planning. For operational scenarios, a subset of representative hours is used to model system operations. They focus on regular and extreme load seasons to capture critical periods without needing to simulate every hour of the year. [41]

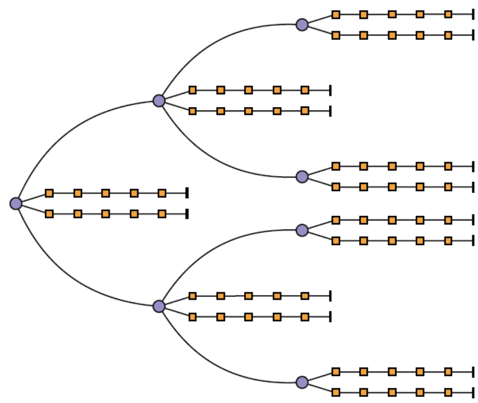

**Figure 2:** Multi-horizon stochastic program with strategic and operational uncertainty in EMPIRE [41].

## 3.2 Optimization Model

The optimization model in EMPIRE aims to minimize total system costs over a long planning horizon, which forms the objective function. This includes both investment and operational costs, where the decision variables focus on expanding generation, storage, transmission infrastructure, and operating energy resources [41].

On the operational time scale, the decision variables govern the system's hourly functions, such as dispatching generation units, operating storage systems, and coordinating regional electricity transfers. The model incorporates various factors, such as transmission and storage efficiency losses and load shedding, to realistically capture energy flows and maintain the balance between supply and demand. [41]

The model operates under several key constraints that guide its decision-making. Investment constraints limit how much generation capacity and transmission infrastructure can be added each year, ensuring that expansions occur gradually over time. Power balance constraints ensure that electricity supply always meets demand at every node on an hourly basis, maintaining system stability. Generation constraints regulate how much energy each unit can produce, with additional restrictions such as ramp-up limits for thermal generators, which control how quickly their output can change. Transmission constraints cap the electricity that can flow between regions based on the capacity of transmission lines and account for transmission losses. Reservoir water availability and seasonal energy constraints both limit hydroelectric generation, ensuring effective year-round use of water resources. Lastly, storage constraints manage the operation of storage systems by controlling their energy levels and accounting for efficiency losses during charging and discharging. [41]

## 3.3 Modeled Technologies

The model incorporates a variety of technologies that contribute to system operations and investment dynamics. These technologies can be grouped into conventional generation, renewable generation, nuclear, hydro, bio, waste-to-energy, storage, and transmission.

Conventional generation technologies include coal, lignite, oil, and gas, which provide dispatchable power to support baseload and peak demands. Among these, open cycle gas turbine (OCGT) is primarily used for peaking, while combined cycle gas turbine (CCGT) is favored for its efficiency in sustained generation. Additionally, carbon capture and storage (CCS) is applied to certain conventional fuels, capturing $CO_2$ emissions to reduce their environmental impact.

Renewable generation technologies, including wind (both onshore and offshore), solar, and geothermal, play a significant role in decarbonization. Offshore wind, in particular, offers high-capacity renewable energy, though subject to variability, while solar complements other sources by providing power during daylight hours. Geothermal energy, by contrast, is a stable source unaffected by weather, enhancing system reliability.

Nuclear power contributes low-carbon electricity, supporting long-term sustainability targets and providing a reliable power supply to the grid. Meanwhile, hydroelectric power includes both reservoir-based and run-of-the-river systems. Reservoir-based hydro provides flexibility and storage potential, while run-of-the-river hydro contributes steady renewable generation without storage capacity.

Bioenergy and waste-to-energy technologies add further flexibility to the system. As dispatchable renewable options, they not only provide power but also address waste management, allowing renewable generation that can be adjusted to meet demand.

Energy storage technologies in the model include hydro pumped storage and lithium-ion BESS. Hydro pump storage offers rapid dispatch capabilities, essential for balancing peak demands, while lithium-ion BESS manages variability in renewable generation by storing excess power and releasing it during high-demand periods.

Lastly, the transmission infrastructure, which consists of high voltage alternating current (HVAC) overhead lines and high voltage direct current (HVDC) cables, is crucial for moving electricity across regions. HVDC cables are particularly suited for long-distance, high-efficiency transmission, facilitating the delivery of renewable energy where it is most needed.

## 3.4 Model Inputs

The model relies on a range of inputs to capture the energy system's economic, technical, and stochastic dynamics. These inputs are organized into three categories, each valuable in enabling the model to simulate the financial and operational complexities of power systems.

Economic parameters are essential for evaluating the financial feasibility of different system configurations. These inputs include discount rates, generation and transmission investment costs, operational expenses, and load-shedding costs [41]. The model also imposes limits on maximum investments in capacity and transmission infrastructure [41]. By accounting for both upfront capital expenditures and ongoing operational costs, EMPIRE enables cost-benefit analyses of various energy system investments [41].

Technology features represent the technical characteristics of the energy system's components. These include aggregated loads and generation capacities for each country, along with seasonal capacity factors for different generation technologies [41]. Generator-specific attributes, such as efficiency and heat rates, are also incorporated [41]. Additionally, transmission losses between regions and pump efficiencies for energy storage systems are considered [41]. These inputs aid in modeling energy flows and operational constraints, enabling EMPIRE to optimize system performance under realistic technical conditions.

Lastly, stochastic scenarios serve as inputs that simulate the uncertain nature of renewable generation and demand. The model generates hourly data series for parameters such as electricity demand, wind power (onshore and offshore), solar, and hydroelectric production [41]. This random scenario generation keeps the statistical properties of the original data, which means that correlations between variables such as load and renewable generation are kept [41].

The scenario generation process begins by selecting a random year from the available dataset. For each season, the model selects a starting hour and uses consecutive hours to populate the seasonal data, preserving temporal relationships within the data. Extreme load seasons, characterized by peak demand or low renewable output, are also modeled to assess system performance during stress. These scenarios ensure that both system-wide and regional events are represented accurately. Once generated, the scenarios are validated to ensure alignment with the statistical properties of the original data. [41]

## 3.5 Model Outputs

The EMPIRE model generates various outputs that provide both strategic and operational insights into the energy system. These outputs help identify optimal investment paths for the system and how such a system operates under different scenarios.

The primary outputs are the investment decisions regarding generation capacity and transmission line expansions [41]. These decisions are made for each investment period, which spans multiple years. For each period, the model indicates how much new capacity should be installed and where upgrades to the transmission network are required to ensure that future demand can be met [41].

On the operational level, the model provides hourly system operation outputs [41]. These include the dispatch schedules for generation units, which show how much electricity each unit should produce during each hour in each operating scenario to meet demand [41]. Additionally, the model tracks power flows between nodes, showing how electricity is transmitted between different regions [41]. This is particularly important for understanding how the grid manages renewable energy variability and demand changes across different areas.

The model also outputs information on energy used for pumping, which refers to the amount of electricity used to operate pumped storage facilities. These facilities store energy by pumping water to higher elevations during periods of low demand and then releasing it to generate electricity during peak demand periods. By tracking this, the model helps assess the role of storage in counteracting the variability in the production of VRE resources. [41]

Another key operational output is load shedding, which occurs when the system cannot meet demand and customers experience power outages [41]. This output reflects how well the system maintains reliability under different scenarios, and minimizing load shedding is a critical objective for ensuring a stable energy supply.

Lastly, the model produces the total system costs, which include both the costs of investments in new infrastructure and the operational costs incurred during each period [41]. These costs are essential for evaluating the economic feasibility of different energy system setups and strategies.

## 3.6 Comparison with other Models

The EMPIRE model has numerous advantages over other frequently used CEMs. While DIMENSION incorporates short-term dispatch decisions, it is a deterministic model that disregards short-term uncertainty. This makes it less appropriate for systems that exhibit significant variability in renewable energy sources.

Another model that incorporates operational decisions is E2M2. However, it optimizes investments in single steps, which restricts its ability to completely evaluate the long-term effects of those decisions across multiple periods. It also lacks the mechanisms necessary to manage the variability of renewable energy and the balancing needs required to maintain system stability, due to its emphasis on electricity market simulations.

The TIMES framework incorporates a two-stage stochastic program that enables strategic decision-making under uncertainty, thereby addressing both short- and long-term dynamics. Nevertheless, its two-stage structure does not permit modelling multi-period investment decisions. Thus, it cannot be used for analyses that require ongoing modifications to long-term strategies as uncertainties evolve.

Despite its value in the optimization of long-term system costs, MESSAGE does not provide a complete representation of short-term operational constraints. Its focus is primarily on strategic investments, which limits its ability to fully integrate the operational dynamics needed for systems with significant renewable energy penetration and energy storage requirements.

In contrast, EMPIRE is the optimal choice for the analysis of renewable energy systems with significant storage and flexibility requirements. The reasoning behind this choice is its ability to seamlessly integrate investment decisions with granular modeling of operational decisions. EMPIRE offers a superior framework for assessing both short-term and long-term strategies in the presence of uncertainty by incorporating the operational uncertainties associated with renewable energy generation and the technical characteristics of various technologies.

The subsequent section provides an in-depth explanation of the specific methods and data that were employed to apply the EMPIRE model to the Nordic region, following the detailed discussion of the model's structure. The section outlines the methodology in which key parameters were defined and how they affect the model's results by concentrating on the Nordic dataset.

# 4 Nordic Adaptation of EMPIRE

The input data for this study is composed of several files and scenario information, which guide the overall functioning of the EMPIRE model. This data includes country-specific parameters, technology characteristics, transmission links, and seasonal scaling for renewable energy resources. Figure 3 provides a visual representation of the overall data flow, showing how raw user input and scenario-generated data are converted into optimization-ready model inputs. In the following subsections, the data used to model the Nordic energy system will be explained in detail.

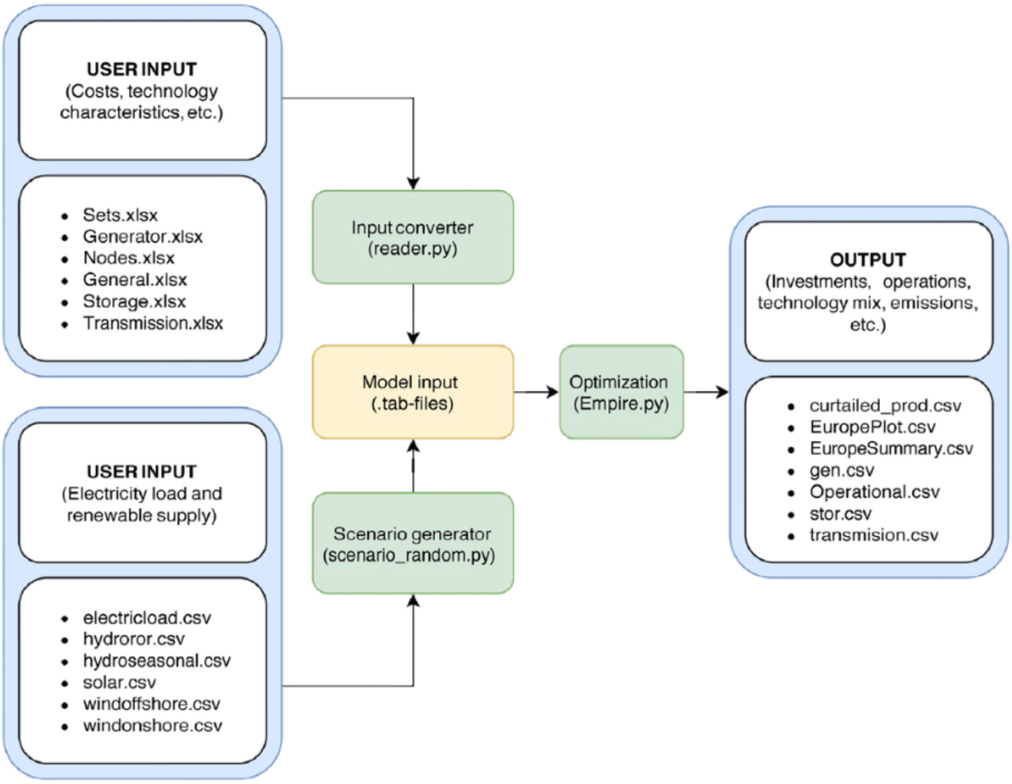


**Figure 3:** Input data structure and flow in the EMPIRE model [9].

## 4.1 Node Structure

The model forms a total of 33 nodes to represent different regions, countries, and offshore wind across Europe, as shown in Table 1. The focus is on the Nordic region, which include Finland, Sweden, Norway, and Denmark. These nodes represent key electricity markets and allow for a thorough analysis of energy flows, generation, and storage within the Nordic energy system. Each country, except Finland, is divided into multiple price areas (SE1-SE4 for Sweden, NO1-NO5 for Norway, and DK1-DK2 for Denmark), reflecting regional differences in electricity prices.

To capture the interactions and dependencies of the Nordic energy system, the model also incorporates nodes for other European countries that are closely linked through transmission lines. Countries such as Germany, Great Britain, Belgium, Poland, the Netherlands, Estonia, Latvia, and Lithuania are included due to their transmission connections to the Nordic grid, which allow for energy exchanges. High-voltage direct current interconnectors link these regions to the Nordic countries, allowing the model to capture cross-border energy flows and accurately represent the interactions between interconnected European energy systems.

Furthermore, specific offshore wind farm clusters have been defined to capture the growing role of offshore wind energy, particularly in the North Sea. These clusters are linked to the transmission systems of the nodes and provide renewable energy resources to the interconnected grid. The offshore wind farm clusters are discussed in further detail in Section 4.4.

| Country Nodes | Offshore Wind Farms Nodes |
|---|---|
| Belgium | Cluster1 |
| DK1 | Cluster2 |
| DK2 | Cluster3 |
| Estonia | Cluster4 |
| Finland | Cluster5 |
| Germany | Cluster6 |
| Great Britain | Cluster7 |
| Latvia | Cluster8 |
| Lithuania | Cluster9 |
| Netherlands | Cluster10 |
| NO1 | Cluster11 |
| NO2 | Cluster12 |
| NO3 | Cluster13 |
| NO4 | |
| NO5 | |
| Poland | |
| SE1 | |
| SE2 | |
| SE3 | |
| SE4 | |

**Table 1:** Nodes part of the Nordic dataset.

## 4.2 Time Horizon

The model evaluates the system's operation over a 10-year horizon, spanning from 2023 to 2033, with operational impacts extending through 2035 to capture the full effect of each investment. Divided into five 2-year investment periods, each period provides an assessment of how strategic investments modify the system to adapt to future demand. Investments are assumed to become immediately available, with no delay or construction time required, allowing resources to be operational as soon as each investment period begins.

## 4.3 Input Data for the Nordic Energy System

This study utilizes a structured set of input data specific to the Nordic energy system, supporting the EMPIRE model's simulation of infrastructure and performance.

A structured summary of each input parameter's function in the model is given in Table 2. It includes crucial details such as cost metrics, capacity constraints, and operational characteristics for transmission, storage, and generation that are necessary for modeling and assessing the Nordic energy system. All data used in the Nordic EMPIRE model is sourced from publicly available datasets, reports, and literature, ensuring transparency and replicability.

**Table 2:** Inputs used in the EMPIRE model and data sources of the Nordic dataset.

| **Data Category** | **Description** | **Source** |
|---|---|---|
| $CO_2$ Price | $CO_2$ prices for each period, expressed in euros per tonne of $CO_2$ (€/t$CO_2$). | [42] |
| Capital Costs | Capital costs for generator technologies , expressed in euros per kilowatt (€/kW) | [43][44] |
| Fixed Operation and Maintenance Costs | Annual operation and maintenance costs for generator technologies, given in euros per kilowatt (€/kW). | [43][44] |
| Variable Operation and Maintenance Costs | Costs per unit of electricity production for generator technologies, specified in euros per megawatt-hour (€/MWh). | [43] |
| Efficiency | Percentage of fuel converted to electricity for generator technologies, expressed as a percentage (%). | [43] |
| Operational Lifespan | Expected operational lifespan for generator technologies, measured in years. | [43] |
| Fuel Costs | Fuel Costs, specified in euros per gigajoule (€/GJ). | [42][45] |
| CCS Costs | Cost of capturing and storing $CO_2$ per tonne, given in euros per tonne of $CO_2$ (€/t$CO_2$). | [46] |
| Initial Generation Capacity | Initial generation capacity of technologies for each node, measured in megawatts (MW). | [47][48][49] |
| Retirement Scale Factor | Percentages of initial capacity that will retire in each investment period for each generation technology. | Linear extrapolation |

Continuation of Table 2

| Data Category | Description | Source |
|---|---|---|
| Resource Limits on Installed Capacity | Resource limits for maximum installed capacity of generators, specified in megawatts (MW). | [50][51][52] |
| Ramp Rate | Rate of output change per hour for thermal generators, given as a percentage of installed capacity per hour (%). | IEA,NEA |
| Generator Availability | Percentage of installed capacity available at any given hour. | IEA,NEA |
| $CO_2$ Emissions Content | $CO_2$ emissions per unit of fuel consumed, specified in kilograms of $CO_2$ per gigajoule (kg $CO_2$/GJ). | [53] |
| Annual Electricity Demand | Annual electricity demand for each node, given in megawatt-hours (MWh). | [54][55] |
| Cost of Lost Load | Economic cost associated with unmet electricity demand, specified in euros per megawatt-hour (€/MWh). | [56] |
| Maximum Hydro Production | Maximum expected annual production from hydro generators, for reservoir-based and run-of-the-river systems, specified in megawatt-hours (MWh). | NREAP |
| Initial Power Capacity | Initial charging/discharging capacity for each node, divided by hydro pump storage or lithium-ion BESS, measured in megawatts (MW). | [47] [57] |
| Power Capital Cost | Cost required to install storage capacity (€/kW). | [58] [59] |
| Power Fixed Operation and Maintenance Cost | Fixed operation and maintenance cost per year for maintaining storage capacity (€/kW). | [59] |
| Power Maximum Built Capacity | Maximum additional storage capacity that can be built per period (MW). | Assumption |
| Energy Capital Cost | Cost required to add energy storage capacity (€/kWh). | [58] [59] |
| Energy Fixed Operation and Maintenance Cost | Fixed operation and maintenance cost per year for energy storage (€/kWh). | Default: 0 |

| Continuation of Table 2 | | |
|---|---|---|
| **Data Category** | **Description** | **Source** |
| Energy Initial Capacity | Initial energy storage capacity for each node, divided by hydro pump storage or lithium-ion BESS, given in megawatt-hours (MWh). | [47] [57] |
| Energy Maximum Built Capacity | Maximum additional energy storage capacity that can be added per period (MWh). | Assumption |
| Energy Maximum Installed Capacity | Maximum total energy storage capacity allowed for each node and storage type, including a 10% increase over existing capacity (MWh). | Assumption |
| Power Maximum Installed Capacity | Maximum allowable storage capacity for charging/discharging built per period,including a 50% increase over installed capacity, measured in megawatts (MW). | Assumption |
| Storage Initial Energy Level | Initial energy level of storage systems as a percentage of their installed energy capacity (%). | Assumption |
| Storage Charging Efficiency | Efficiency of energy storage during the charging process, expressed as a percentage (%). | Assumption |
| Storage Discharging Efficiency | Efficiency of energy release during the discharging process, expressed as a percentage (%). | Assumption |
| Storage Power to Energy Ratio | Required ratio of installed power to energy storage capacity for dependent storage systems (MW/MWh). | Assumption |
| Storage Self-Discharge Efficiency | Hourly percentage of energy loss (self-discharge) from storage systems (%). | Assumption |
| Lifetime | Anticipated operational lifespan of storage systems (years). | [60] |
| Transmission Line Efficiency | Percentage of electricity transmitted that reaches the destination node, expressed as a percentage (%). | Default: 0.97 |

| Continuation of Table 2 | | |
|---|---|---|
| **Data Category** | **Description** | **Source** |
| Maximum Transmission Capacity Built | Maximum transmission capacity that can be constructed between nodes within a period, specified in megawatts (MW). | Assumption |
| Transmission Line Length | Physical length of the transmission line between nodes, measured in kilometers (km). | Distances defined by map |
| Transmission Capital Cost | Investment cost per MW-km for transmission lines, including HVAC overhead lines and HVDC cables, specified in euros per megawatt-kilometer (€/MW-km). | Default: 0 |
| Transmission Operation and Maintenance Cost | Annual operation and maintenance cost for transmission lines, specified in euros per megawatt (€/MW). | Default: 0 |
| Initial Transmission Capacity | Initial transmission capacity between nodes within a period, measured in megawatts (MW). | [61] |
| Transmission Line Lifespan | Expected operational lifespan of transmission lines between nodes, specified in years. | Default: 40 years |

## 4.4 Offshore Wind Farm Clusters

The offshore wind farm data used in this study was obtained from the Global Wind Power Tracker [48]. This dataset provides information about wind farms around the world. Figure 4 depicts the 122 operational offshore wind farms considered for this analysis, located in the Nordic region and surrounding areas.

Given the large number of wind farms, it was necessary to group them into clusters for the sake of computational tractability. Modeling each wind farm as a distinct node would have significantly increased computational complexity, making the model potentially unmanageable or preventing it from solving. To overcome this, the $k$-means clustering algorithm was applied to group the wind farms based on their geographical proximity. This approach allowed for the inclusion of all wind farms in the model while maintaining a manageable number of nodes (see Figure 5).


**Figure 4:** Operational offshore wind farms considered in the study.

$K$-means clustering is an unsupervised machine learning algorithm used to partition a dataset into a predefined number of clusters, $k$. The algorithm works iteratively to assign data points to clusters based on their distance from the cluster centroids. The process begins by randomly selecting $k$ data points as initial centroids. Each point is assigned to the cluster whose centroid is closest, calculated using Euclidean distance. The centroids are then recalculated based on the new cluster assignments, and this process repeats until the centroids stabilize. [62]

One challenge with $k$-means clustering is determining the optimal number of clusters, $k$. If too few clusters are chosen, the wind farms may be too geographically dispersed within a cluster, reducing model accuracy. Conversely, if too many clusters are used, the efficiency gained from clustering is reduced. The elbow method was used to identify a reasonable number of clusters, based on the Within-Cluster Sum of Squares (WCSS), which measures the variance within each cluster [62]. The goal is to minimize the WCSS while avoiding an excessive number of clusters [62].


**Figure 5:** Resulting clusters of offshore wind farms after applying k-means clustering.

The elbow method involves running the $k$-means algorithm for a range of $k$ values and plotting the WCSS for each value of $k$ [62]. As the number of clusters increases, the WCSS decreases, but the rate of decrease slows at a certain point, forming an "elbow" in the plot [62]. This point is taken to represent the optimal number of clusters, beyond which adding more clusters results in diminishing returns [62].

Figure 5 illustrates the 13 clusters identified in this study, determined using the elbow method. This number was chosen to provide clear geographical groupings while maintaining computational efficiency. This clustering approach allows the model to capture the distinct characteristics of different geographical areas without the complexity of representing each wind farm as an individual node.

It is important to note that the model does not generate new nodes when simulating future investments. This means that, while the model can expand capacity within the established clusters, it cannot create new offshore wind farms in previously undeveloped locations. Consequently, all new investments in offshore wind are constrained to the geographic areas where current wind farms are located, reflecting an assumption that future capacity expansions will occur within or near existing infrastructure.

## 4.5 Scenario Data

The scenario data used in this study originates from the Europe v51 dataset included in the EMPIRE code repository [63]. Table 3 summarizes the scenario data used in the model. This dataset provides hourly values for profiles such as electric load, hydro run-of-river, hydro seasonal, solar, wind onshore, and wind offshore for each applicable node, spanning from January 1, 2015, through December 31, 2019.

To align the data with the study's timeline, values from 2015–2019 were reindexed to represent the years 2023–2027. Renewable energy profiles (wind, solar, and hydro), represented by capacity factors (the ratio of actual output to maximum potential output), were assumed to remain similar over time. This approach considers variations in renewable generation patterns from 2015–2019 to be representative of the period up to 2035.

For demand, the pattern of fluctuations (daily and seasonal variations) was assumed to remain unchanged, while the total demand level was adjusted to align with forecasts provided in the input data.

For countries with multiple price zones, including Sweden (SE1–SE4), Norway (NO1–NO5), and Denmark (DK1, DK2), the data was divided to represent each price zone accurately. The scaling factors used for profiles were assigned the same value across all price zones within a country, ensuring consistency. For numeric profiles, such as energy capacities or production figures, the values were simply divided among the zones according to the same ratios as the changes in hydropower production across those zones.

**Table 3:** Overview of scenario data in the Nordic dataset.

| **Name** | **Description** |
|---|---|
| Electric Load Profile | Hourly electricity demand data for each node. |
| Wind Profile (Onshore) | Hourly wind generation data for onshore wind farms. |
| Wind Profile (Offshore) | Hourly wind generation data for offshore wind farms. |
| Solar Profile | Hourly Solar Generation Data. |
| Hydro Profile | Seasonal and hourly hydroelectric generation data. |

# 5 Results

The results of this study provide insights into the projected development of BESS and renewable energy integration in the Nordic countries from 2023 to 2033. This section begins with an analysis of BESS capacity distribution across the Nordic region, which highlights the differences in storage adoption among the countries by 2033.

## 5.1 BESS Deployment

### 5.1.1 BESS Capacity in 2033

Figure 6 displays the projected BESS capacities in the Nordic countries for the operational period 2033-2035, with power capacities (MW) shown on the left and energy capacities (MWh) on the right. The model indicates that Sweden has the highest installed BESS capacities, both in terms of power and energy. In contrast, Norway, Finland, and Denmark show considerably lower levels of installed BESS capacity in both metrics.

The maps indicate that Sweden's installed energy capacity extends significantly beyond those of its neighboring countries, with a pronounced difference in scale.

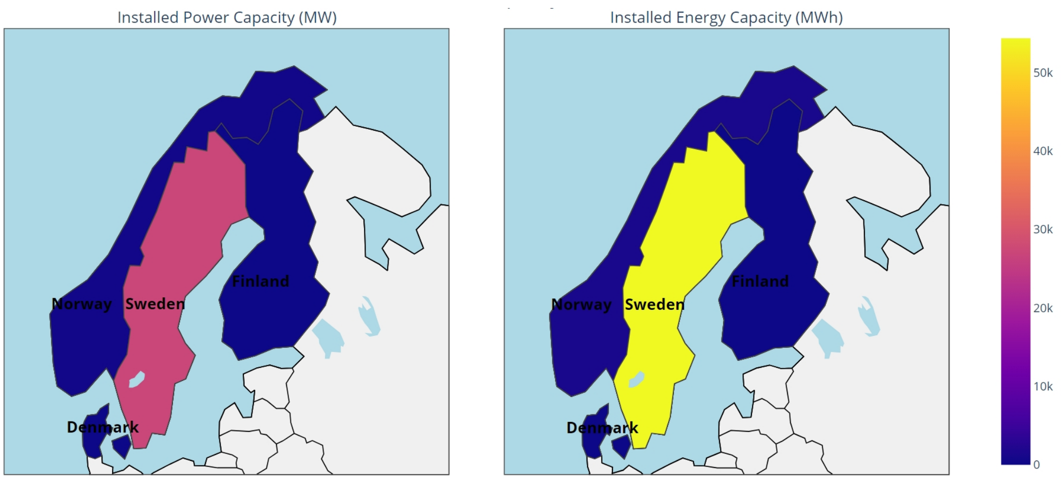


**Figure 6:** Projected installed BESS capacities by 2033 in the Nordic region. The left panel shows installed power capacity (MW), while the right panel displays installed energy capacity (MWh).

### 5.1.2 Limited BESS Investments in Other Nordic Countries

Figure 7 illustrates the progression of BESS investments across the modeled periods. These plots highlight Sweden's dominance in BESS adoption, supported by significant capacity additions across all investment periods. In contrast, Norway exhibits negligible investments during the first four periods, similar to the patterns observed for Denmark and Finland throughout the entire modeled horizon. However, Norway displays a small but notable increase in both energy and power capacities in the final investment period, marking its only measurable adoption of BESS. Denmark and Finland remain consistently below the threshold of 1 MW or 1 MWh, rendering their contributions insignificant for further analysis.

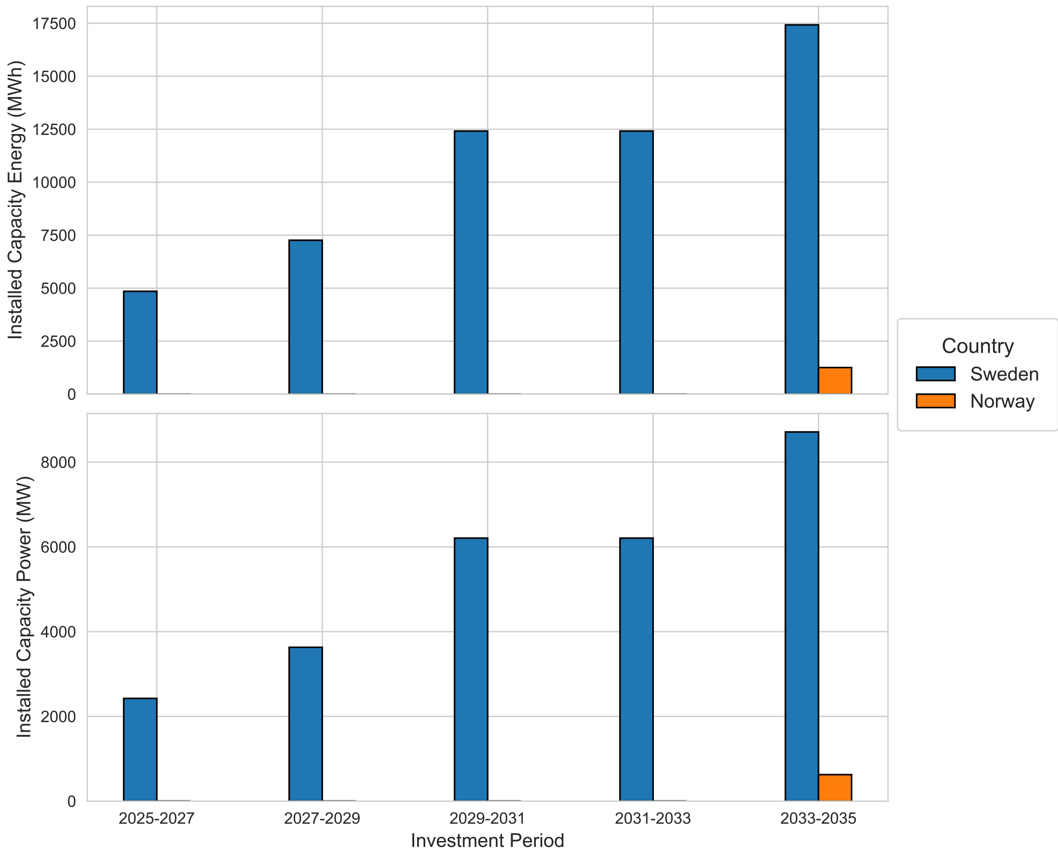


**Figure 7:** Total installed BESS capacity by investment period in each country. The top plot shows the progression of installed energy capacity (MWh), and the bottom plot shows the progression of installed power capacity (MW).

While Norway's BESS investments are minimal even with the inclusion of the the last operational period, it does align with its abundant hydro power storage capacity. Hydro power in Norway provides both energy storage and grid stability, dampening the need for large-scale battery investments and acting as a natural flexibility resource. Although temporal variations in Norway's hydro capacity are not visible in the plots, the capacities remain consistently high across all periods. Table 4 provides Norway's pumped hydro storage capacities for power and energy across the modeled periods.

**Table 4:** Norway's Pumped Hydro Storage Installed Capacities

| Investment period | Installed power capacity (MW) | Installed energy capacity (MWh) |
|---|---|---|
| 2025-2027 | 1329.50 | 4908400.00 |
| 2027-2029 | 1329.50 | 4908400.00 |
| 2029-2031 | 1329.50 | 4908400.00 |
| 2031-2033 | 1329.50 | 4908400.00 |
| 2033-2035 | 1329.50 | 4908400.00 |

## 5.2 Renewable Energy Investments across the Nordics

Figures 8, 9 and 10 illustrate the modeled progression of installed capacities for solar, wind, and run-of-river hydro across the Nordic countries. The plots provide a comparative view of how renewable energy sources evolve in each country.

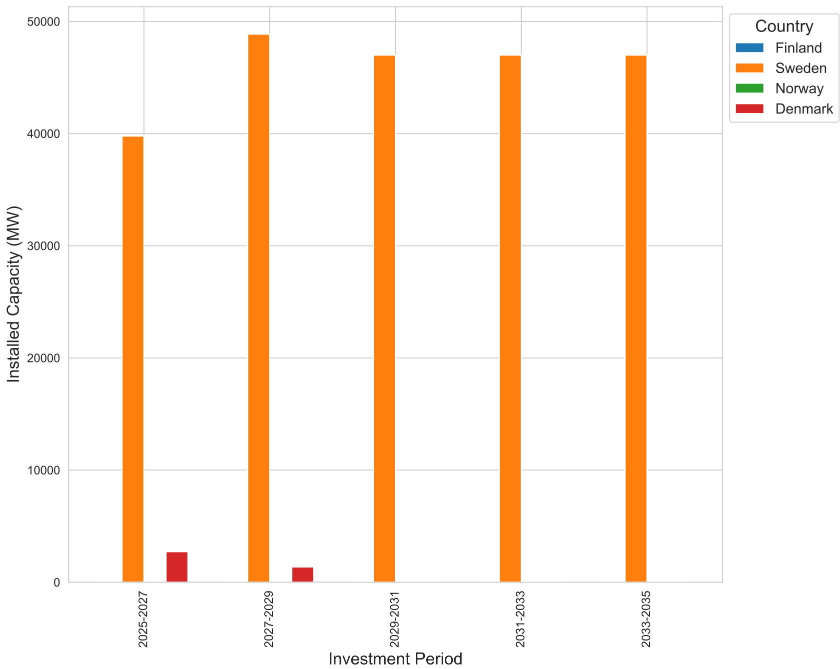


**Figure 8:** Installed solar capacity by investment period in each country.

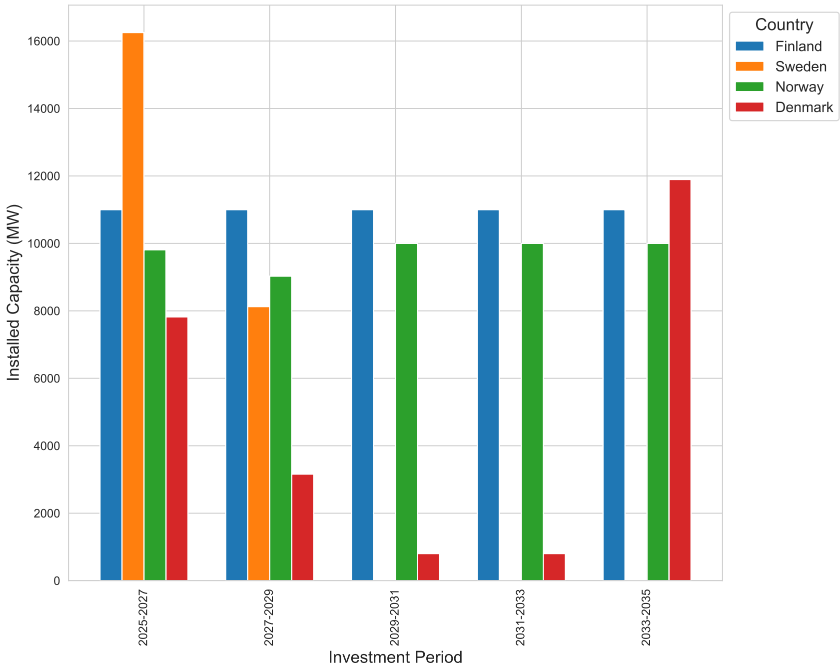


**Figure 9:** Installed wind (onshore and offshore) capacity by investment period in each country.

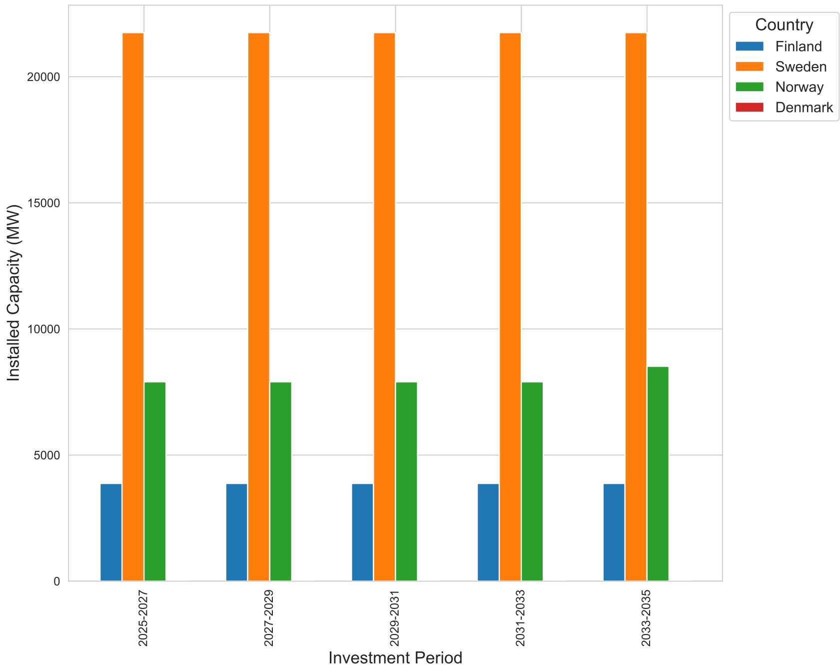


**Figure 10:** Installed run-of-river hydro capacity by investment period in each country.

As seen in Figure 8, Sweden consistently leads the Nordic region in installed solar capacity across all investment periods.

Figure 9 illustrates Sweden's initial leadership in wind capacity, with the highest levels during the first investment period. However, Sweden's wind capacity declines significantly after the first period and disappears entirely after the second. Denmark, on the other hand, stands out for its focus on wind energy, with its capacity showing variability and a notable increase in the final period. This aligns with Denmark's reliance on wind as its primary renewable energy source. Norway and Finland show more constant wind capacities over the timeline compared to the significant changes seen in Sweden and Denmark.

In Figure 10, Sweden's dominance in run-of-river hydro capacity is evident, with stable and high levels maintained consistently over the timeline. Norway ranks second with slightly lower but equally stable capacity, while Finland comes third with moderate and constant hydro capacity throughout the timeline. Denmark's hydro capacity, on the other hand, is negligible.

These renewable energy patterns align closely with the earlier BESS capacity analysis. Sweden's significant investment in a diversified renewable portfolio, encompassing solar, wind, and hydro, necessitates the adoption of BESS to enhance grid flexibility and manage variability across different energy sources. In contrast, Norway's reliance on hydro, which inherently provides a natural form of energy storage, minimizes its need for additional BESS investments.

## 5.3 Energy Mixes across the Nordics

Figures 11 and 12 illustrate the installed capacities by technology type across the Nordic countries, highlighting how each nation's unique resource base and energy strategy shapes its energy mix. Figure 11 focuses on Sweden and Finland, while Figure 12 examines Norway and Denmark.

In Figure 11, Sweden emerges as a leader in solar and hydro run-of-river capacities, with nuclear providing a stable contribution throughout the timeline. The high initial capacity of offshore wind, which disappears after the second period, suggests a strategic shift toward solar and hydro resources. Finland's energy profile complements stable hydro and growing onshore wind with an increasing reliance on gas technologies such as CCGT and OCGT in later periods.

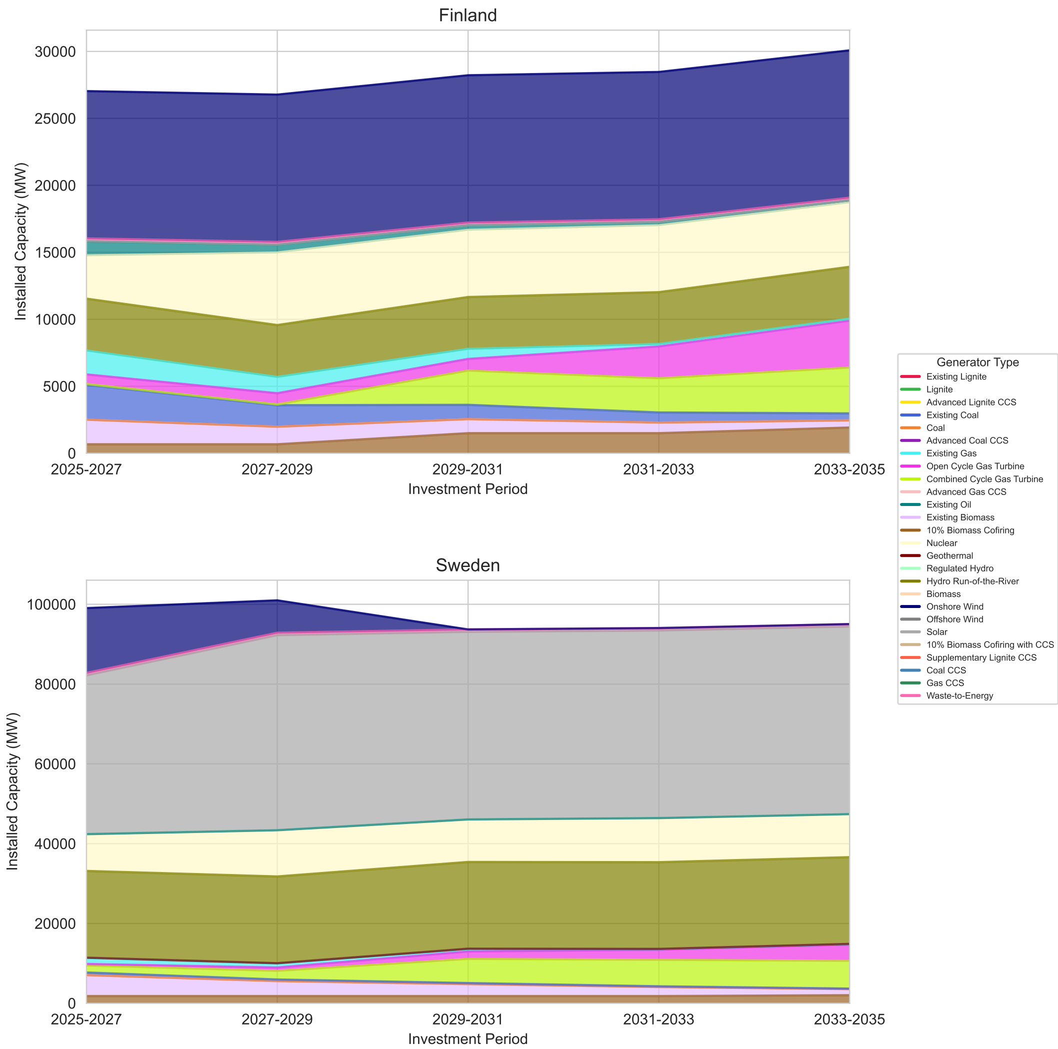


**Figure 11:** Installed generation capacity (MW) by investment period for Sweden and Finland.

Figure 12 reveals Norway's energy mix, heavily dominated by hydropower, where regulated hydro serves as the largest contributor alongside steady inputs from hydro run-of-river and onshore wind. However, a gradual increase in CCGT capacity in the final period hints at a growing need for additional dispatchable flexibility, which aligns with Norway's minimal yet notable adoption of BESS toward the end of the timeline. Denmark demonstrates a more dynamic capacity mix, characterized by variability in earlier periods and a late increase in onshore wind and OCGT capacities after the third period. The rising role of OCGT reflects the growing flexibility demands of a system heavily reliant on wind energy. The absence of offshore wind in later periods highlights a strategic shift to other technologies to address system requirements.

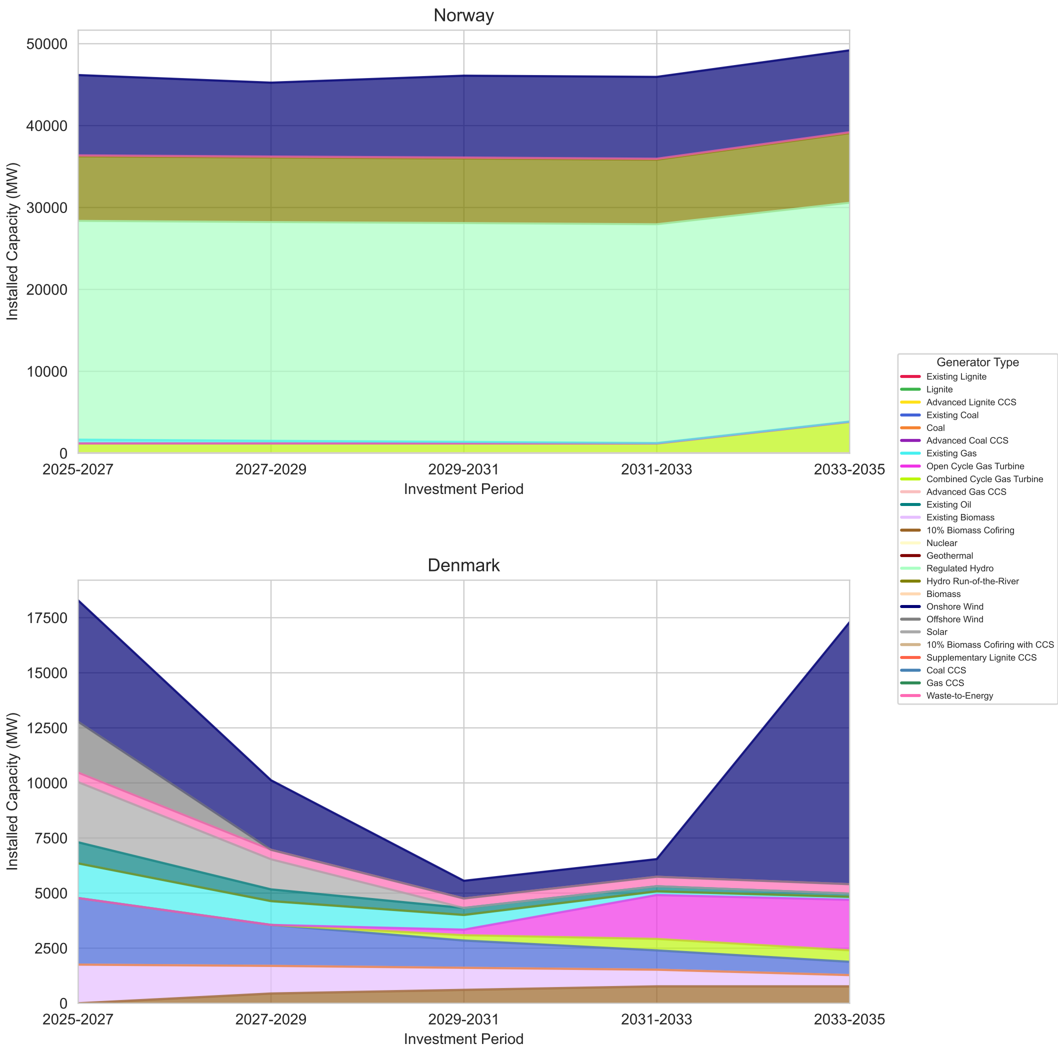


**Figure 12:** Installed generation capacity (MW) by investment period for Norway and Denmark.

## 5.4 Curtailment and Flexibility Needs

Figure 13 illustrates the curtailment levels of VRE for the Nordic countries over the modeled investment periods.

VRE curtailment levels remain lowest in Sweden throughout the periods. This outcome is associated with the substantial installed BESS capacities, as shown in Figure 7, and significant hydro run-of-river capacity within its system. The combination of these resources provides a strong mechanism for absorbing and releasing excess renewable energy, effectively reducing curtailment. These results highlight the high renewable energy utilization achievable through a well-integrated system of storage and flexibility.

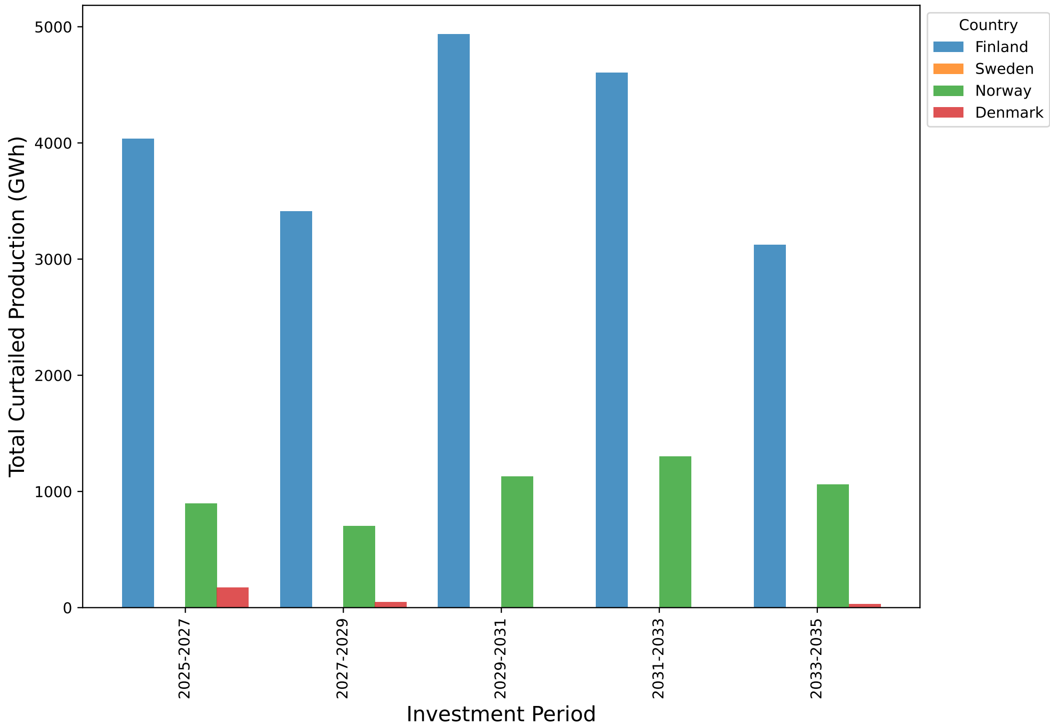


**Figure 13:** Total curtailed production (GWh) by investment period across the Nordic countries.

In contrast, Finland is associated with the highest levels of curtailment among the Nordic countries. Despite the reliance on onshore wind, nuclear, and hydro run-of-river, the limited BESS capacity appears to hinder the ability to store and manage excess VRE output. This results in significant power curtailment, raising questions as to why the model does not prioritize BESS investments in Finland to mitigate curtailment. The continued use of other flexibility options, such as gas technologies observed in later periods, suggests that the model evaluates these alternatives as a more cost-effective or complementary solution to Finland's energy system. However, the high curtailment levels indicate a potential area for improvement, where targeted BESS investments could enhance renewable integration and reduce energy losses.

Norway, which exhibits moderate curtailment levels, reflects its reliance on hydroelectricity as the primary flexibility resource. The lack of significant BESS investments is attributed to the stability and abundance of hydropower capacity. Hydropower naturally provides flexible management of VRE output. However, the small-scale use of BESS during the final investment period suggests that increasing reliance on renewable energy may create localized challenges that cannot be fully addressed by Norway's hydro resources.

Denmark consistently exhibits minimal curtailment levels throughout the periods despite negligible BESS capacity. This outcome is likely due to the ability to manage energy surpluses and deficits effectively, reducing the reliance on local storage solutions and keeping curtailment levels low.

While these strategies mitigate VRE curtailment to varying degrees, the effectiveness of such measures often hinges on the underlying transmission infrastructure. The next section delves into how transmission capacity and inter-zonal flows influence the region's ability to balance renewable generation and manage variability.

## 5.5 Transmission Analysis Across the Nordic Region

The transmission results from the model highlight distinct interconnection patterns across the Nordic region, as depicted in Figures 14, 15, 16, and 17.

Figure 14 shows that Finland's primary transmission pathways are the Estonia-Finland and Finland-NO4 connections, which handle significant annual volumes. These interconnections allow the system to manage demand fluctuations without deploying substantial BESS capacity. However, moderate transmission losses, particularly on the Estonia-Finland route, suggest opportunities for improving efficiency.

Sweden's transmission network, illustrated in Figure 15, demonstrates a diverse set of flows, with NO1-SE3 emerging as the highest-volume connection. This strong interconnection supports Sweden's large-scale integration of renewables such as solar, wind onshore, and hydro run-of-river. The model results highlight how Sweden's combination of transmission capacity and significant BESS installations allows for effective internal balancing and low curtailment levels. Additional connections, such as DK1-SE3 and Lithuania-SE4, emphasize the integration of cross-border flows to manage energy variability.

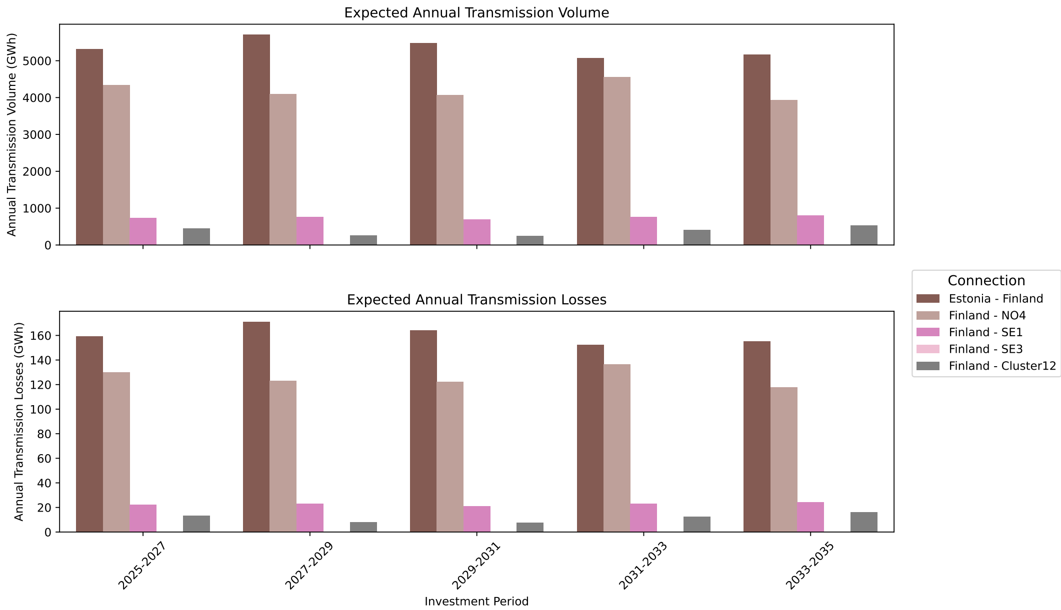


**Figure 14:** Transmission analysis for Finland showing expected annual transmission volumes and losses.

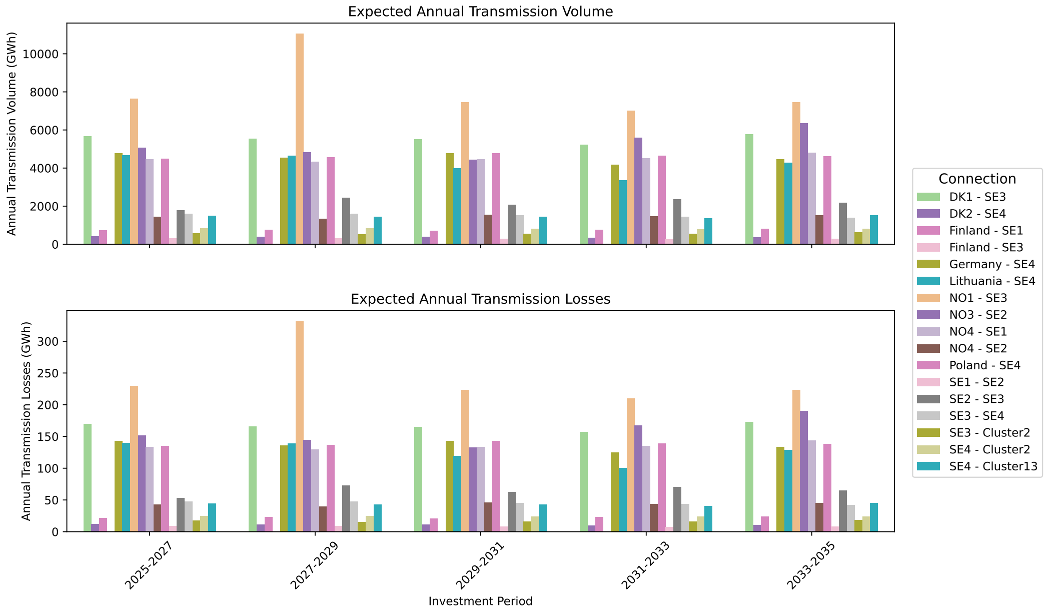


**Figure 15:** Transmission analysis for Sweden showing expected annual transmission volumes and losses.

Norway's hydro-dominated energy system is reflected in Figure 16, which highlights high-volume interconnections such as DK1-NO2, NO1-NO3, and Germany-NO2. These interconnections facilitate the export of hydroelectric surpluses, enabling Norway to act as a balancing hub within the region. The model indicates that while hydro resources provide the primary flexibility, a small-scale adoption of BESS in the final investment period could address localized challenges as renewable energy penetration increases.

As shown in Figure 17, Denmark relies on external interconnections, particularly DK1-Germany and DK1-NO2, to manage the variability of its wind-dominated energy system. These connections effectively manage surplus wind generation, limiting the need for local storage. The model also indicates minimal transmission between Denmark's internal zones (DK1 and DK2), suggesting independent operation of these regions with significant dependence on cross-border flows for balancing.

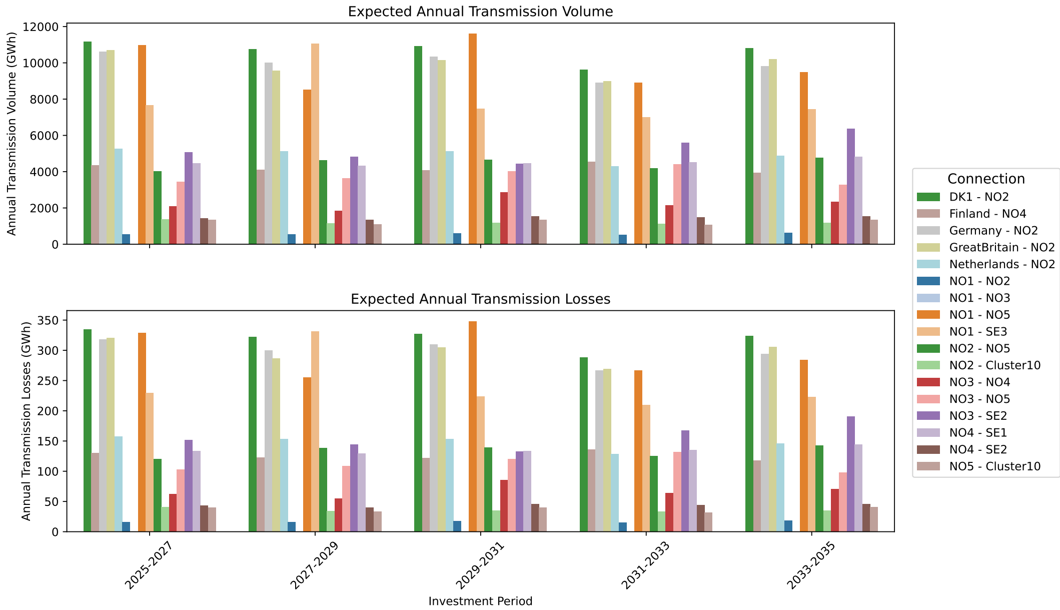


**Figure 16:** Transmission analysis for Norway showing expected annual transmission volumes and losses.

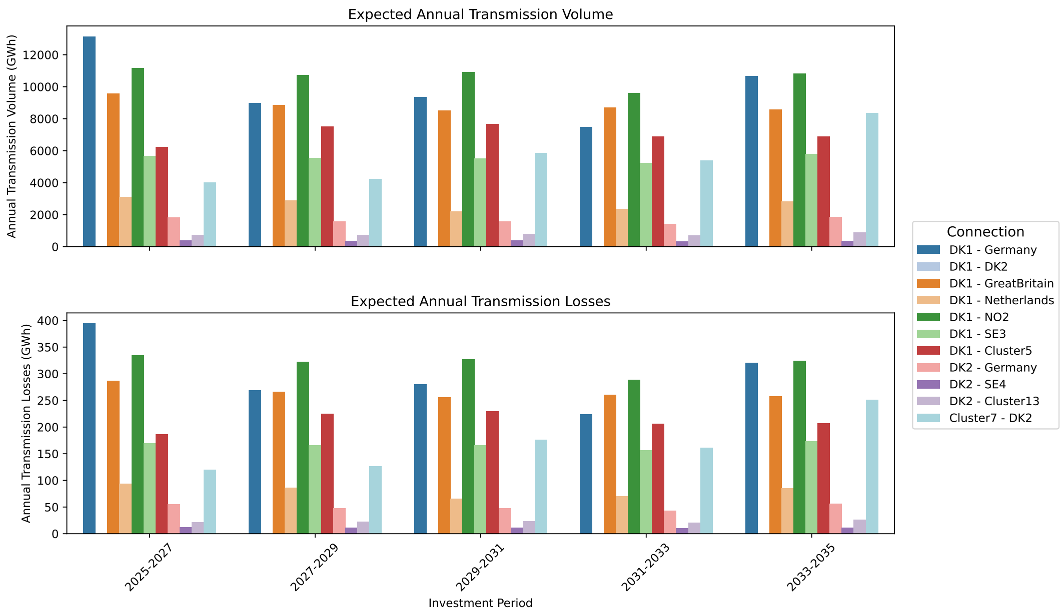


**Figure 17:** Transmission analysis for Denmark showing expected annual transmission volumes and losses.

These findings underscore how transmission infrastructure shapes the role and development of BESS across the Nordic region. Strong interconnections often serve as a substitute for localized storage, as seen in Finland and Denmark, where external flows reduce the immediate need for large-scale BESS deployment. Conversely, countries such as Sweden leverage both transmission and BESS to balance diverse renewable portfolios and manage internal energy flows, emphasizing the complementary nature of these technologies. Norway's reliance on hydro flexibility further illustrates how existing resources can delay or reduce the need for BESS, but it also highlights potential gaps in addressing future challenges as renewable penetration deepens.

## 5.6 Summary

The results of this study show different approaches to integrating renewable energy and managing flexibility across the Nordic region from 2023 to 2033. The adoption of BESS varies widely, with higher investments in areas that rely on a mix of solar, wind, and hydroelectric power. In these regions, BESS helps reduce power curtailment and improves grid stability, while the existing transmission networks support the balancing of renewable energy across zones.

In areas with large hydroelectric resources, the natural storage provided by hydro systems reduces the need for BESS. Pumped hydro capacities remain consistently high, offering a reliable way to manage energy supply and demand. These regions also benefit from strong transmission links that allow them to export surplus energy efficiently. On the other hand, areas with limited BESS and a focus on specific technologies, such as wind power, experience higher energy curtailment.

Systems that depend heavily on wind energy manage variability through cross-border transmission rather than local storage. These connections are key to balancing energy production and demand. A shift away from offshore wind in some areas, in favor of other technologies, reflects cost-driven optimization within the model, as it prioritizes the most economical solutions based on the given inputs and constraints.

# 6 Conclusion

This thesis set out to evaluate the role of BESS in supporting the integration of renewable energy across the Nordic energy system, aligning with the ambitious climate and energy targets established by each country. However, the results reveal a more complex and uneven adoption landscape, highlighting the need for region-specific strategies.

The model's findings indicate that BESS adoption is concentrated almost entirely in Sweden, driven by its diverse renewable energy portfolio of solar, wind, and hydro run-of-river, which creates significant grid balancing demands. In contrast, the other Nordic countries show negligible BESS development by 2033. Norway's reliance on its abundant hydro resources, which inherently provide natural flexibility, minimizes the need for BESS investments. Denmark and Finland, despite their renewable energy ambitions, adopt alternative strategies. Notably, Finland's reliance on gas technologies increases in later periods, providing critical flexibility to manage renewable variability. These gas technologies, while effective in the short term, underscore the trade-offs between immediate system stability and long-term decarbonization goals.

The reliance on gas technologies in Finland and the minimal use of BESS suggest an opportunity for a hybrid approach. Targeted BESS investments could address curtailment challenges and improve renewable utilization, complementing existing gas infrastructure. Denmark, on the other hand, leverages strong transmission interconnections to balance variability, maintaining low curtailment levels despite minimal local storage. These diverse approaches reflect the importance of tailoring energy strategies to each country's unique resource base and flexibility needs.

From a policy perspective, these findings provide important insights. Sweden's potential for BESS integration highlights the importance of coupling diversified renewable portfolios with storage investments. Norway's hydro-dominated system showcases the value of leveraging natural flexibility resources, while Finland's and Denmark's strategies emphasize the role of gas and transmission infrastructure in the absence of extensive BESS deployment. Strengthening cross-border transmission networks emerges as a potential priority, enabling the region to collectively manage variability and enhance renewable integration.

Despite these insights, the study is subject to several limitations. The modeling approach relies on static assumptions for renewable generation patterns and energy demand, which may not fully capture future technological advancements or shifts in market dynamics. Additionally, the exclusion of offshore wind farm developments beyond existing clusters and the static treatment of $CO_2$ pricing reduce the scope for exploring emerging trends in the energy landscape. The model's reliance on temporal aggregation to reduce computational complexity may also obscure finer operational details, particularly during extreme load periods.

Future research should address these limitations by incorporating dynamic modeling of offshore wind developments, exploring variable $CO_2$ pricing scenarios, and refining the treatment of operational uncertainties. A deeper analysis of the economic and policy incentives required to promote BESS adoption in countries with low uptake, such as Finland and Denmark, could further enhance understanding of the region's energy transition. Additionally, integrating advanced flexibility options, such as hydrogen storage and demand-side management, could provide a more comprehensive framework for optimizing the Nordic energy system.

While the results provide valuable insights, they diverge from initial expectations that BESS would see widespread adoption across the Nordic region. This outcome underscores the importance of considering country-specific factors in energy planning models. This research contributes to the broader understanding of energy storage in renewable-rich systems, offering a framework for evaluating its role in diverse contexts. By addressing its limitations and building on the recommendations outlined, future work can better support the Nordic region's transition to a sustainable, low-carbon energy system.

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