MULTI-RENEWABLE EUROPEAN POWER SYSTEM: WAVE ENERGY INTEGRATION

By

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Life comes in waves

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Executive summary

The release of the 6th assessment report by the IPCC has highlighted once more the urgent need to decarbonize our energy systems if we are to reach the global agreement to limit global warming below 2 degrees below pre-industrial levels (United Nations, 2015). Rapid deployment and exploitation of all available renewable energy resources is a necessary step towards the substitution of fossil fuels and decarbonization of our energy systems. For Europe, this has been further highlighted by the recent developments Russian-Ukraine war, with the European Commission highlighting the double urgency to transform Europe's energy system, by ending the dependence of Europe on Russian fossil fuels and tackling the climate crisis through measures such as energy savings, diversification of energy supplies, and accelerated roll-out of renewable energy.

Multi-renewable energy systems, which must consider emerging technologies that exploit other available renewable energy resources, have the potential to reduce the variability of current mature renewable technologies such as solar and wind, increase power availability, diversify the electricity supply, and ultimately accelerate the substitution of fossil fuels. Ocean energy technologies can represent an important part of these multi-renewable generation low-carbon energy systems, given their vast and yet untapped source of renewable energy medium. They are increasingly being perceived as an important piece of future energy systems, given they are characterized by stable generation profiles, predictability, and high energy density. Among the different ocean energy technologies, wave energy shows strong potential to support carbon reduction targets and meet expected increases in electricity demand. It is considered one of the most dense, predictable, and persistent energy sources, with multiple regions exposed to the wave energy resource.

This researched performed an exploratory investigation of the impacts and interactions of wave energy in a wider context under future cost-optimal and multi-renewable configurations of the European transmission network. This was achieved, first, by expanding the renewable energy capabilities of the existing open-source PyPSA-Eur, energy system model and dataset of the European power system at the transmission level covering the full ENTSO-E area, to include the wave energy resource. And second, by simulating a set of future, cost-optimal, and multi-renewable European power systems at 2030, 2040, and 2050 horizons employing a greenfield optimization approach and considering cost-reduction potentials of wave energy and other generating technologies.

The novel expansion of the renewable energy capabilities of the PyPSA-Eur model allows for the assessment of the wave energy resource according to specific wave energy converters (WEC) across Europe's coastlines for a respective year. Allowing to estimate the renewable wave energy capacity potentials restricted by depth, packing rate, and land availability, derive renewable wave generation availability time series of the WEC devices according to their power matrices and the characterized sea-states, and ultimately consider the wave energy resource and technologies in a cost-based power flow optimization of the European transmission grid.

Regarding the resource assessment, it was found that on pure land availability criteria the wave energy resource is the most abundant within Europe, especially in coastline countries, having the highest geographic potential reaching an aggregated 20.3 TW. The North Sea was found to have large land availability and be a highly productive site for the Farshore and Nearshore devices, while some regions in the Baltic Sea were found to be attractive for the Shallow device.

Regarding the set of multi-renewable power system scenarios modelled at the horizons of 2030, 2040, and 2050, at a European level, solar and onshore wind dominated the deployed generating technologies installed extensively across Europe representing between 48-47% and 45-47% respectively of the overall generation mix across the different horizons. WEC Shallow cost reductions estimated with a learning curve approach seem to have provided a cost-competitive advantage in some locations as its capacity grew from only 12 MW in 2030 up to 30.9 GW in 2050, installed mainly in the Black and Mediterranean Seas. While Offshore wind (DC) was essentially only installed in Romania in the Black Sea with a capacity of around 11.8GW and remained relatively constant throughout the horizons. Other offshore technologies were minimally installed. The dominance of solar and wind characterizes the behavior of the overall system, and it was found that the deployment of the different storage technologies in specific locations is correlated to the deployment of these two mature renewable technologies. With solar capacity moderately correlated with installed battery capacity and onshore wind capacity strongly correlated with installed hydrogen storage capacity.

At a regional level, Romania, Albania, and Hungary's configurations were compared against each other, chosen based on the diversity of their energy portfolio, similar aggregated generation capacity, and their share of wave energy capacity. Romania resulted as the country with the most diversified generation portfolio. Interestingly, Romania is also the country with the least amount of storage capacity. However, no correlation was found between a multi-renewable energy portfolio and storage capacity needs. Meanwhile, Albania's portfolio consists of approximately equal parts of solar and wave energy, while Hungary has a solar-dominant generation portfolio. Romania was found to be the country with the most stable available supply of electricity throughout the year, however, it significantly imports electricity during midday hours. It was found that it is actually importing cheaper electricity from elsewhere, most likely solar, given the time of the day, and curtailing its own, more expensive, electricity generation. Albania highlighted the potential benefits of solar and wave energy combined, given their complimentary nature of supply, enabling it to be a net exporter of electricity for the region. Lastly, Hungary is heavily dependent on electricity imports, both for satisfying its own electricity demand and for charging its storage technologies, and only exporting during peak solar generation periods.

This research identified relevant benefits attributed to wave energy, but more specifically to multi-renewable energy portfolios. Wave energy, characterized by predictability, high availability, and high energy density, can play an important role in achieving carbon emission reduction targets while supplying energy demand, broadening the energy mix, increasing the availability of renewable power, increase energy security. Wave energy technologies can be integrated with other renewable generators to provide higher availability of supply, smoothen the power output, reduce variability, and increases the consistency of the regional generation profile. Additionally, it was found that cross-border transmission capacity is very relevant to future multi-renewable energy systems, as it is a cost-effective investment that supports the system's ability to capture and fully take advantage of renewable energy resources unevenly distributed across Europe.

The open-source and transparent nature of PyPSA-Eur allowed for further improvements and the novel addition of the wave energy resource and it is hoped that it will enable further investigations and discussions of future renewable power systems and the potential role that wave energy may play.

1. Introduction

1.1 Background

The release of the 6th assessment report by the IPCC has highlighted once more the urgent need to decarbonize our energy systems if we are to reach the global agreement to limit global warming below 2 degrees below pre-industrial levels (United Nations, 2015). Rapid deployment and exploitation of all available renewable energy resources is a necessary step towards the substitution of fossil fuels and decarbonization of our energy systems.

The energy transition is currently being led by mature renewables such as hydro, solar, and wind, but they come with setbacks of their own due to their intermittent nature, leading to challenges to maintain flexibility and power stability. These setbacks will be further enhanced as their share in the electricity system increases. Although electricity storage can offer short-term flexibility for these mature renewables, multi-renewable energy systems, which must consider emerging technologies that exploit other available renewable energy resources, have the potential to reduce the variability of these technologies, increase power availability and accelerate the substitution of fossil fuels. (Lavidas & Blok, 2021)

Marine technologies can represent an important part of these multi-renewable generation low-carbon energy systems. Ocean energy and marine energy are collective terms that refer to any form of energy derived from the kinetic, potential, thermal and chemical energy of the sea. Oceans are potentially the largest source of renewable energy medium, as the oceans cover around ¾ of the world's surface area. The theoretical resource potential of ocean energy is so vast that it could meet present and projected global electricity demand well into the future. An analysis by the International Renewable Energy Agency assessed the aggregated value of the theoretical resource of all energy technologies combined at between 45,000 terawatt-hours (TWh) and 130,000 TWh per year (IRENA, 2020). This is more than double the amount of the current global electricity demand of 25,027 TWh in 2019 (IEA, 2020).

Marine energy is increasingly being perceived as an important piece of future energy systems, given they are characterized by stable generation profile, predictability, and high energy density. Furthermore, marine renewable energy resources are more persistent and have higher temporal availability compared to solar and wind resources. (Bhattacharya et al. 2021; IRENA 2020a; Lehmann et al. 2016; Reikard, Robertson, and Bidlot 2015). As mature renewable technologies increase their share in existing energy systems, the intermittency of solar and wind introduces volatility and unpredictability to the system, leading to potential mismatches between demand and supply. Given this, marine energy can support the stabilization of renewable energy power systems with multiple variable renewable energy sources (IRENA 2020a) (Lehmann et al. 2016a). In their work, Bhattacharya et al. (2018), highlight that a system with solar, wind, and marine energy presents reduced generation volatility than a system with only solar and wind, which translate into alleviating balancing costs and reducing price volatility. Furthermore, stating that it is expected that these benefits to be more pronounced as renewable energy deployment increases.

Furthermore, multi-renewable energy systems, which include marine energy, are linked to the advancement of multiple United Nations Sustainable Development Goals (SDGs), such as SDG 7- Affordable and Clean energy, and SDG 13 - Climate Action (IRENA, 2020a). Furthermore, renewable energy penetration increases energy diversity, supports decarbonization targets, and reduces import dependency. The latter is particularly relevant for Europe given the recent developments of the Russian-Ukraine war and the respective implications on energy imports, highlighting the need to end Europe's dependence on Russian fossil fuels.

Among the different ocean energy technologies, wave energy shows strong potential to bridge the gap between carbon reduction targets and the increasing energy demand. Wave energy is currently an untapped resource, and while the exact global wave power estimate is still under debate, it is considered to be between 29,500 TWh/yr and 32,000 TWh/yr (Guo & Ringwood, 2021; IRENA, 2020b; Reguero et al., 2015). It is the second largest among all ocean renewable energy sources (Aderinto & Li, 2018). It is one of the most dense, predictable, and persistent energy sources. Furthermore, multiple regions and countries are exposed to it and can exploit wave and other ocean resources to meet their energy needs and decarbonization targets. Especially relevant for islands and remote coastal areas, which commonly have high and volatile energy costs and limited land availability.

Nonetheless, wave energy, and other MRE technologies, still face relevant technical and non-technical challenges, the primary ones being its higher levelized cost of electricity (LCOE) and survivability. Mainly due to the high capital investments needed as these technologies need to be resilient against a multitude of weather events. However, by not only focusing on LCOE and emphasizing some of the advantages it may provide, especially under multi-renewable energy systems, research can help change the perception and accelerate the deployment of this type of technologies, as the ocean remains the most abundant yet untapped source of energy in the planet.

Most research on wave energy has focused on its continued development, testing, and increasing the Technology Readiness Level for tidal and wave energy converters. Research has focused on identifying the most suitable sites for exploiting ocean energy, the efficiency of existing technologies, the amount of power generated, and the potential environmental impact of these technologies. (Wilberforce et al., 2019). Recently, research has focused on potential grid applications of ocean energy under high-renewable energy scenarios. Although studies have identified relative advantages from integrating wave energy in conjunction with existing renewable technologies, such as the potential to reduce the balancing requirements of the power system of specific sites (Bhattacharya et al. 2021b; Zeyringer et al. 2018), the authors highlight that further research and detailed techno-economic assessments are required to better understand and confirm the potential impacts on power system operation. International bodies like IRENA and the IPCC further highlight that the integration of ocean energy into wider energy networks needs to be further assessed under a wider context (IPCC, 2011a).

1.2 Thesis objectives

As mentioned, further research and assessment of the integration of ocean renewable energies into our power systems are necessary to fully understand the potential and implications of these types of converters. To achieve this, the proposed research will seek to assess the implications of integrating wave energy converters in the European Electricity Grid by further developing Python for Power System Analysis (PyPSA), an existing open-source toolbox for simulating and optimizing power systems, and more specifically PyPSA-Eur, a dynamic energy system model and dataset of the European power system built on PyPSA and coupling it with metocean climate data. The methodology will look to integrate and develop novel subroutines and representative models and conversion functions for certain ocean energy converters in the existing PyPSA-Eur energy system model. The research will specifically focus on wave energy converters and their interaction with the grid, and other variable renewable energy technologies under high-share & multi-renewable energy scenarios.

The objective of this research is to understand the general system dynamics of a future multi-renewable European power system and the potential role that wave energy may play within these future power systems. An exploratory investigation was performed of the potential impacts and interactions of wave energy in a wider context under future cost-optimal and multi-renewable configurations of the European transmission network, with the purpose to better understand and optimize the future deployment and investment in the generation and transmission capacities of the European Energy System. The proposed project is scientifically and societally relevant as it seeks to contribute to the intersection between the field of future renewable power systems and the field of marine renewable energy. It will seek to provide a realistic representation of the potential of wave energy and its interactions under multi-renewable energy systems. This research, as well as the tools developed, will hopefully serve as a steppingstone for further investigations and assessments on the potential of wave energy and its role in future power systems, hopefully accelerating the energy transition and supporting the accomplishment of the SDGs, such as SDG 7 and SDG 13.

1.3 Research Questions & Sub-questions

The following questions research questions to be answered by this research are:

a. What are suitable representative models and subroutines of wave energy converters to be integrated into the PyPSA framework and the PyPSA-Eur energy system model?
b. What are the geographic energy potentials of wave energy in Europe considering different wave energy converters paired with climate and metocean conditions?
c. How may the technology costs of wave energy converters develop by 2030, 2040, and 2050? What is their effect on cost-optimal configurations of a multi-renewable European power system?
d. What are the general system dynamics of a multi-renewable European power system which considers the deployment of wave energy converters? And how do the network components evolve through the 2030, 2040, and 2050 horizons?
e. What is the impact of transmission capacity expansion under cost-optimal configurations of a multi-renewable European power system?
f. What is the potential role of wave energy in future cost-optimal configurations of the European transmission network under a multi-renewable power system?

2. Literature Review

This chapter begins with a general overview of the ongoing energy transition in Europe is provided. It is followed by a summary of current research perspectives regarding high-share renewable energy systems. Subsequently, a detailed overview of wave energy and wave energy converters is provided. Lastly, an introduction to power system modelling and analysis is presented, followed by a justification, and a detailed description of the modelling tool selected for this research.

2.1 Renewable Energy Transition in Europe

The European Commission (EC) has set ambitious targets to become climate-neutral by 2050 through its European Green Deal (European Commission, 2019)and become the first continent with a net-zero greenhouse gas economy. This deal is in line with Europe's commitment under the Paris Agreement to keep global temperatures below 2ºC below preindustrial levels. As part of the European Green Deal, on March 2020, the commission proposed the first European Climate Law to set the climate neutrality target into law (Rowan & Pogue, 2021).

Through the Green Deal Directives, the EC seeks to increase cooperation among member States to strengthen and diversify their energy resources. Among a wide variety of actions across all sectors and industries, the expansion and improvement of transmission interconnections across states as well as the integration of energy markets is a crucial step to guarantee energy security and neutrality goals. (Child et al., 2019). Furthermore, the European Commission has proposed increased funding to support efforts in cross-border cooperation on renewable energy projects and trans-European network infrastructure, as part of the long-term EU budget 2021-2027 (European Commission, 2018).

In recent developments, the urgency of the transition has been further advanced by the implications of the Russian-Ukraine war and the sanctions implemented by NATO and European Allies. Through the REPOwerEU (European Commission, 2022c), the European Commission has highlighted the double urgency to transform Europe's energy system, by ending the dependence of Europe on Russian fossil fuels and tackling the climate crisis through measures such as energy savings, diversification of energy supplies, and accelerated roll-out of renewable energy. This transformation seeks to strengthen economic growth, security, and climate action for Europe and our partners. (European Commission, 2022c)

By 2020, the European Union (EU) achieved and surpassed its target to fulfill at least 20% of its total energy consumption from renewables. In fact, 22.1% of the EU gross final energy consumption came from renewable sources, an increase from 9.6 % in 2004. (Eurostat, 2020). Figure 2.1 showcases the share of renewables in gross final energy consumption by country against the targets set for individual countries. While the EU as a whole surpassed its 2020 renewable energy target, some member states did not meet their individual targets and had to use statistical transfers to meet them. Statistical transfers refer to agreements between states to transfer specified amounts of energy from renewable sources from one member to another Member (Eurostat, 2020).

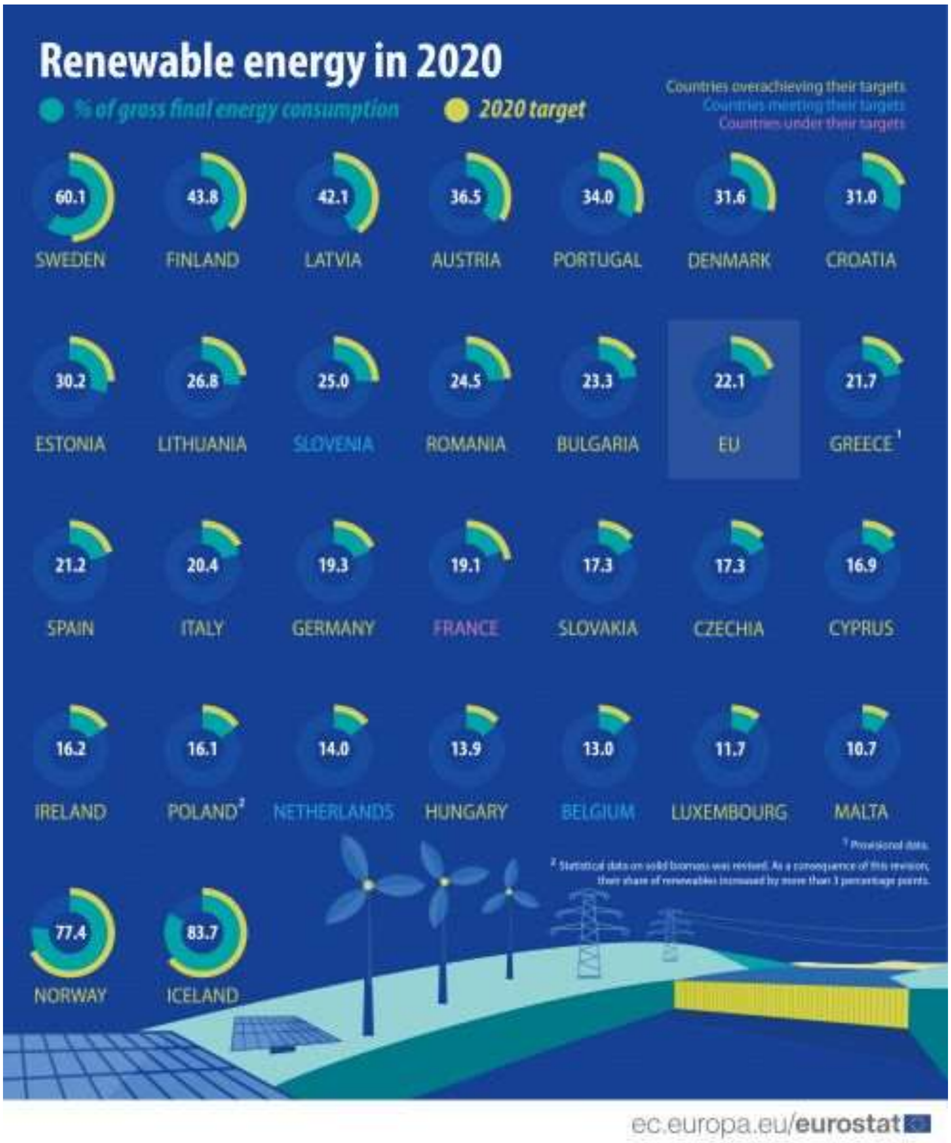

Figure 2.1 Share of energy from renewable sources, 2020
Source: (Eurostat, 2020)

Regarding electricity consumption, a 37.5% share of gross electricity consumption was made up of renewable energy sources in 2020, Of which 36% came from wind renewable energy, 33% from hydropower, 14% from solar power, 8% from solid biofuels, and 7% from other renewable sources. Solar power has been the fastest-growing renewable, increasing from 7.4 TWh (1% of electricity consumption) in 2008 to 144.2 TWh (14% of electricity consumption) in 2020. (Eurostat, 2020). Among EU member states Austria and Sweden achieved the highest renewable electricity shares with 78.2% and 74.5, respectively. Meanwhile, Norway and Iceland produced more electricity than they consumed from renewable sources in 2020, leading to shares higher than 100% and hence contributing to their exporting of electricity.

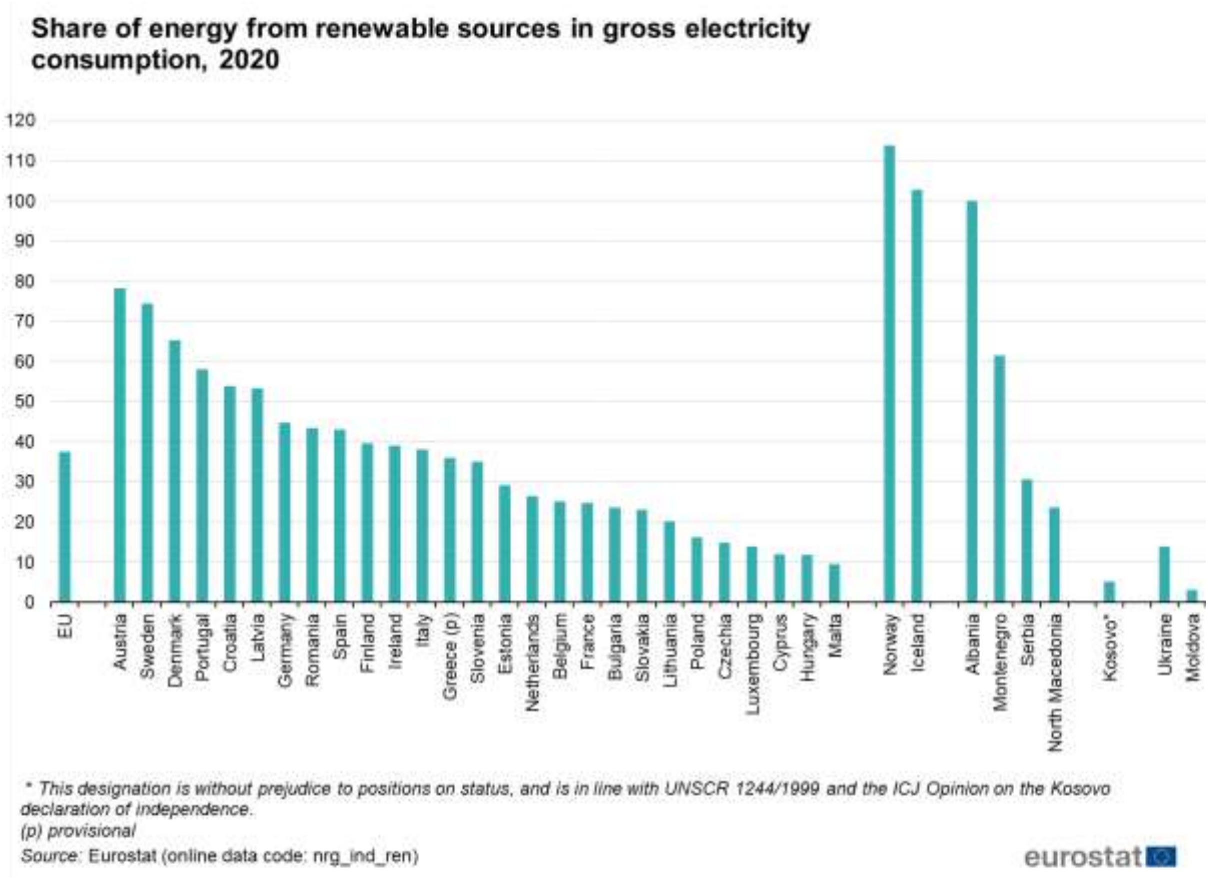

Figure 2.2 Share of energy from renewable sources in gross electricity consumption, 2020
Source: (Eurostat, 2020)

Building on the achieved target of 20% for 2020, the Renewable Energy Directive established a binding renewable energy target for the EU of at least 32% by 2030. This directive has room for a possible upwards revision by 2023 and a proposal to raise it to 40% is currently underway (European Commission, 2022b).

2.2 Status and perspectives for renewable energy systems

In line with the global ambitions set under the Paris agreement of 2015 of limiting the temperature increase to 1.5°C above preindustrial levels and other regional and local decarbonization targets, such as the European union's green New Deal, research on the feasibility and the large-scale deployment of renewable energy systems is a major focus not only of academia but a variety of stakeholders involved in policy, industry, and global decision making. In fact, the importance and urgency of the renewable energy transition are further highlighted by the UN's Sustainable Development Goals (SDG), an international framework to achieve a sustainable future for the planet through international cooperation. Specifically, SDG Goal #7 addresses he global goal on energy through three key targets; affordable energy services; a substantial increase of the share of renewable energy in the energy mix; and doubling the rate of improvement in energy efficiency (Gielen et al., 2019; United Nations, 2022a). Furthermore, the transition to 100% renewable energy systems has the potential to contribute to the fulfillment of SDG Goal #6 Clean Water and Sanitation, Goal #9 Industry, innovation & Infrastructure, Goal# 11 Sustainable Cities and Communities, Goal #12 Responsible Production and Consumption, and Goal #13 Climate Action (Hansen et al., 2019; United Nations, 2022b).

Ambitions for 100% Renewable electricity are gaining momentum and various examples across a variety of stakeholders can be found. Numerous countries have pledged either to achieve net zero emissions from greenhouse gases or achieve carbon-neutrality targets. Countries like Canada, Austria, United Kingdom, and Nepal pledged net-zero emissions by 2050, while Argentina, Japan, and South Africa are among the ones that seek carbon neutrality by 2050. China, one of the world's largest emitters has pledged carbon neutrality by 2060. Furthermore, not only countries are seeking to decarbonize their electricity needs. Urban and regional commitments are also increasing. Around 830 cities in 72 countries have adopted renewable targets, with around 600 of them setting targets for 100% renewable energy at different timelines. In addition, businesses and corporations are also committing to the energy transition. By 2021, 300 corporations worldwide joined the RE100 initiative and committed to satisfying their energy needs with 100% renewable electricity (REN21, 2021).

In fact, in the year 2020, renewables achieved a 29% share in the global electricity mix, the highest share in history, and capacity continues to be added. 278.3 GW of renewable power capacity was added in 2020, 270 GW in 2021, and it is expected that in 2022, 279.6 GW of additional net renewable capacity will be added by International Energy Agency estimates. One of the main factors of this is the significant drop in the costs of renewable energy, primarily solar photovoltaics (PV) and wind energy, over the last decade.

The levelized cost of electricity (LCOE) of utility-scale solar PV fell 85% between 2010 and 2020 achieving a price of 0.057 USD/kWh. Meanwhile, the LCOE of onshore wind power fell by 54% to 0.041 057 USD/kWh, offshore wind by 48% to 0.084 057 USD/kWh, and concentrated solar power (CSP) by 68% to 0.108 057 USD/kWh in the same period(International Energy Agency 2021). Leveraging on the increasing cost-competitiveness of renewable energy, as well as political, social, and even stakeholder pressure, major energy companies are now shifting and diversifying their portfolios by investing in the renewable energy sector and investing in energy storage, electric mobility, and distribution solutions.

As documented in the previous section, many commitments and pledges from various stakeholders and decision-makers have shown the current trend and momentum to achieve 100% renewable energy systems, and research follows this trend. Hansen et al (Hansen et al., 2019) reviewed 181 peer-reviewed journal articles related to 100% Renewable energy studies over the last decades. As stated by the authors no uniform definition of a 100% renewable energy system exists.

In many cases, such as this current research, focus is exclusively on the electricity sector, while other literature includes the entire energy system including transport, industry, and residential energy consumption. The research field of 100% renewable energy established itself around the 2000s and, in line with global climate commitments and increased public awareness, it has become an increased researched topic since the early 2010s, and indicates an increasing trend. Figure 2.3 showcases the articles reviewed by the authors.

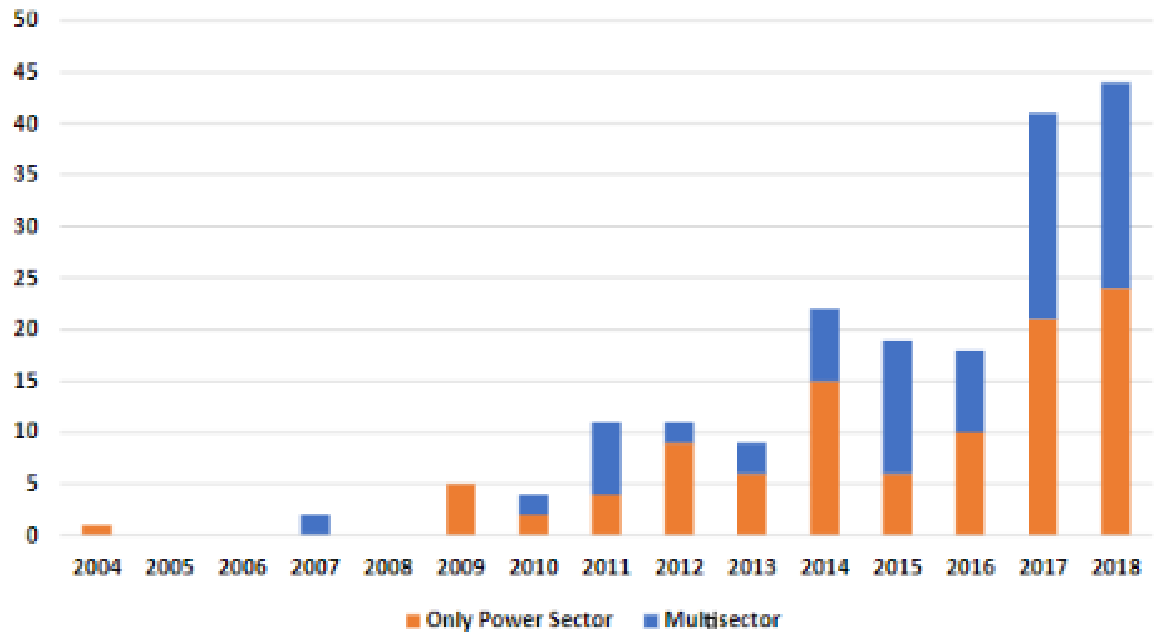

Figure 2.3 Number of 100% Renewable Energy studies for countries, regions, and globally by publication year
Source: (Hansen et al., 2019)

Research has focused on selected regions of the globe, with country or national-scale studies being the most common scope. The most researched region in the world is Europe and is the only world region where trans-national studies are employed regularly. Meanwhile, regions like South America, Sub-Saharan Africa, Eurasia, Northeast Asia, and India have not been yet thoroughly researched.

Hourly energy modeling has been the core methodology for a large number of studies given the variability and flexibility of large-scale integration of variable renewable resources, such as wind and PV. The hourly methodology allows to explore the interactions between the different resources as well as the storage options on an hour-by-hour basis. This allows for a sufficient level of detail to assess the required system flexibility by involving the variable renewable generators, storage, dispatchable generators, and the grid, among others. Furthermore, most recent research has focused on the integration of other energy sectors besides electricity, as well as cross-border integration. It is expected that this expansion of scope will provide insights into how cooperation between countries and sectors can lead to improved utilization of infrastructure, storage, and generators, as well as increased flexibility of the system.

The majority of studies reviewed by Hansen et al, found that 100% Renewable electricity systems are technically feasible, especially for the electricity sector. Furthermore, the authors highlight that an increasing number of studies are integrating other sectors, reflecting the integration of future energy systems. Nonetheless, Heard et al. (2017) have questioned the actual feasibility of 100% renewable electricity systems demonstrated in 24 studies, claiming no empirical or historical evidence, as well as a lack of sufficient technical proven feasibility according to the authors, proposed criteria regarding: (1) consistency with mainstream energy-demand forecasts; (2) simulating supply to meet demand reliably at hourly, half-hourly, and five-minute timescales, with resilience to extreme climate events; (3) identifying necessary transmission and distribution requirements; and (4) maintaining the provision of essential ancillary services. However, T. W. Brown et al. (2018a), respond to Heard et al. (2017) conclusions by questioning their proposed criteria. T. W. Brown et al. (2018a) consider that although the chosen feasibility criteria are important, they are not critical for the viability or feasibility of the renewable systems presented in the studies. Addressing Heard et al. issues with economically viable and existing alternatives such as dispatchable capacity for peak loads, grid expansions, and synchronous compensators for ancillary services. Furthermore, they show that high share renewable energy systems are both feasible and economically viable concerning future demand projections which consider electrification of heating, transport, and industrial sectors, highlighting reduced consumption of primary energy due to reduced energy losses due inherent to fossil fuel use.

Lastly, energy security remains an important aspect to consider also when dealing with renewable energy systems. The challenges posed by climate change and air pollution highlight the need to decarbonize our energy systems and displace fossil-based resources for our energy supplies. Furthermore, the recent developments of the Russian-Ukraine war have highlighted Europe's strong dependencies on imported primary energy resources and the geo-political risks they involve. This has resulted in a stronger push toward the diversification of energy supplies and an accelerated rollout of renewable energy within Europe (European Commission, 2022c).

Although energy security is a complex and multidimensional concept, in essence, it can be defined as the uninterrupted availability of energy sources at an available price, emphasizing resilience to sudden changes in the supply-demand balance (IEA, 2019a). Diversity and dependence are two main energy supply domains, with the former related to a country's capability to produce its own energy needs and the latter related to the variety of its energy portfolio. Diversification assumes that a more diverse energy supply is a more secure one, as a country is less reliant on a single type of energy and the system becomes less sensitive to disturbances (de Rosa et al., 2022).

Renewable energy has various implications for energy security, of which only some of them are mentioned here. First and foremost, renewable energy is produced from non-depletable sources, highlighting it as a major advantage towards long-term supply, given that they are exploited at a sustainable rate. Secondly, the deployment of renewable technologies is linked to the diversification of energy supply, particularly as countries have set targets towards increasing their share within their portfolio. On the other hand, in the short term, the variable nature and dependence on weather conditions of renewable energy involves challenges towards the balance of supply and demand. These challenges can be addressed with technical solutions such as energy storage, increased transmission capacity, and interdependencies between regions. Grid expansion allows dealing with the geographical and temporal variability of renewable sources, as supply can be transferred from currently producing regions to regions limited by weather. Nonetheless, although these alternatives increase energy security among renewables, it implies a relevant trade-off with economic efficiency. Although this trade-off is not exclusive to renewable energy systems (de Rosa et al., 2022; Johansson, 2013).

For Europe, the renewable energy transition supports decarbonization targets, increases the diversity of the energy mix, and reduces import dependency, improving energy security. Nonetheless, it also represents relevant challenges, particularly in the short term, as large penetration of renewables cannot be easily sustained with the current energy infrastructure, and relevant investments are needed, highlighting energy storage and grid expansion. Furthermore, interdependencies among EU states become relevant, with cross-border interconnection playing a relevant role in satisfying energy demand and mitigating a lack of supply, allowing the capture of renewable energy where it is available and carrying it to where it is not. These challenges require coordinated and long-term planning, political commitment and will, and significant investment, while also ensuring affordability, competitiveness, and other social aspects.

2.3 Wave Energy

2.3.1 Background

Ocean energy or marine energy are collective terms that refer to any form of energy derived from the kinetic, potential, thermal and chemical energy of the sea. Oceans are potentially the largest source of renewable energy medium, as the oceans cover around ¾ of the world’s surface area.

Most of the solar radiation is captured by the ocean, creating thermal gradients. Gravitational forces from the Earth-Moon-Sun system form a tidal range, which results in water flows in coastal regions. Evaporation creates salinity and chemical gradients from the differences between fresh and saline water and kinetic energy from the wind is transferred to the surface of the ocean, creating waves. Ocean energy technologies are categorized by the resource that is used to generate energy. The IPCC (2011) identifies the following sources of energy: Waves, Tidal Currents, Tidal Range Ocean Thermal Energy Conversion (OTEC), Ocean Currents, and Salinity Gradients (osmotic power).

The theoretical resource potential of ocean energy is so vast that it could meet present and projected global electricity demand well into the future and it is increasingly perceived as an essential piece of the necessary transition to decarbonize our energy systems. Given its predictability and stable generation, it is theorized that it has the potential to provide a more stabilized grid if integrated with other renewable energy sources, such as wind and solar PV, it has the potential to stabilize grids and smoothen the power output (IRENA, 2020b).

The vast amount of energy in the ocean has the potential to supply the world's energy demands. (Wilberforce et al., 2019). An analysis by the International Renewable Energy Agency assessed the aggregated value of the theoretical resource of all energy technologies combined at between 45,000 terawatt-hours (TWh) and 130,000 TWh per year (IRENA, 2020). This is more than double the amount of the current global electricity demand of 25,027 TWh in 2019(IEA, 2020).

Among the different ocean energy technologies, wave energy shows the potential to bridge the gap between carbon reduction targets and the increasing energy demand. Wave energy is currently an untapped resource, and while the exact global wave power estimate is still under debate, it is between 29,500 TWh/yr and 32,000 TWh/yr (Guo & Ringwood, 2021; IRENA, 2020b; Reguero et al., 2015).

Wave energy, in combination with other renewable technologies, can play an important role in achieving carbon emission reduction targets while supplying energy demand. To meet EU’s climate neutrality targets, the EU commission through the EU Strategy on Offshore Renewable Energy seeks to increase Europe’s offshore and ocean energy capacity, setting a target for 2050 of 300 GW of offshore wind capacity and 40 GW of ocean energy, inclusive of wave energy (European Commission, 2020a). Furthermore, Ocean Energy Systems (OES) member countries seek to install 300 GW of wave and tidal energy capacity across the globe. (Huckerby et al., 2016).

Multiple advantages have been identified for wave power. Wave power is considered a high energy-dense and predictable resource characterized by high availability. Furthermore, wave energy technologies can be integrated with offshore solar and wind powerplants as a complementary resource that smoothens the power output and can reduce the variability of generation. Additionally, wave energy technologies are considered to have reduced environmental impacts as well as reduced visual impacts compared to wind turbines (Fusco et al., 2010; Guo & Ringwood, 2021; Lavidas & Blok, 2021).

2.3.2 Wave Energy Resource

Waves occur over a vast range of scales, from long-period waves with a period of several hours. However, waves suitable for electricity generation and considered under the "wave energy" context are wind waves or swell waves, which are characterized by periods in the range of 2-25 s. Locally generated waves by wind are called "wind waves", while waves that have propagated spatially far from where they were generated are called "swell waves" (Neill & Hashemi, 2018).

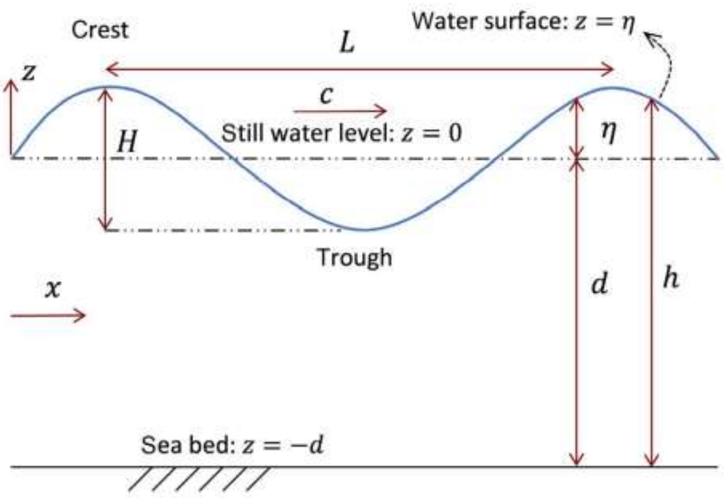

Figure 2.4 Schematic of a monochromatic sinusoidal wave and important wave parameters
Source:(Neill & Hashemi, 2018)

Different properties exist to characterize waves, and many are common to naturally occurring waves. As seen in Figure 2.4, considering linear theory, a wave in represented by a sinusoidal profile, the maximum displacement of the wave from still water is the wave amplitude (a), while wave height (H) is two times the amplitude ($2a$), ergo the distance between the crest and trough. The wavelength (L) is the distance between two consecutive wave crests (or troughs). The time between the two successive wave crests is the wave period (T) and its inverse is the wave frequency ($1/T$). A parameter commonly reported and used during this research is significant wave height (Hs) which is defined as the average height of the highest one-third of the waves on record (Neill & Hashemi, 2018).

In the context of wave energy, resource assessments mainly focus on characterizing the dominant metocean conditions and the energy potential. These are of critical importance in determining the power production potential, the optimal design of devices, and deployment characteristics at particular locations (Guillou et al., 2020; Guo & Ringwood, 2021; Neill & Hashemi, 2018).

2.3.2.1 Wave Power Calculation

As summarized by Guillou et al (2020), the amount of energy from waves reaching a given location is denoted as wave power density (flux or potential per length of unit crest), defined as the integral of the wave energy spectrum

$$P = \rho g \int_0^{2\pi} \int_0^{\infty} c_g(\sigma)\, E(\sigma,\theta)\, d\sigma\, d\theta \tag{2.1}$$

Where ρ is the density of water, g is the acceleration due to gravity, E is the wave energy density distributed over intrinsic frequencies σ and propagation directions θ, and c_g is the group velocity. The wave energy density (E) is the total potential energy of encompassed in a wave per unit surface area averaged over a wave period, and the group velocity (c_g) is the speed of wave energy propagation (Neill & Hashemi, 2018).

Nonetheless, another formulation can be adopted to calculate the wave power density, given the difficulty to gather the distribution of E over the spectra (directions and frequencies). Large-scale assessments commonly rely on the deep water assumption.

Deep waters, characterized by

$$kd \gg 1 \tag{2.2}$$

where d is the water depth and k is the wave number, the group velocity is approximated as

$$c_g = {}^{g}/_{4\pi f} \tag{2.3}$$

with wave frequency (f). With this approximation, formulation (2.1) is reformulated as a function of significant wave height (H_s) and the wave energy period (T_e). For a given wave spectrum H_s and T_e are estimated from spectral moments as

$$H_s = 4\sqrt{m_0} \tag{2.4}$$

$$T_e = {}^{m_{-1}}/_{m_0} \tag{2.5}$$

where m_i is the i_{th} moment of the spectrum, defined as

$$m_i = \int_0^{\infty} f^i\, E(f)\, df \tag{2.6}$$

Therefore, the wave power density (formulation 2.1) can be written as

$$P = \frac{\rho g^2}{64\pi}\, T_e\, H_s^{\,2} \tag{2.7}$$

2.3.2.2 Wave resource assessment and variability

Refined wave resource assessments are of critical importance to identify favorable locations for wave energy exploitation and optimize the design and costs of WECs according to the environmental conditions of those locations (Guillou et al., 2020). Nonetheless, this important process commonly requires a significant amount of data to characterize both spatially and temporally the wave spectrum. Different available data and methods are employed to achieve this.

Relevant data for wave resource assessment includes in situ observations, hindcast databases, and reanalysis databases obtained from large-scale numerical models. While in situ observations are the most accurate representations of the wave conditions, they are dependent on a network of wave buoys and are not always located at points of interest and their measurements only cover specific time periods.

Satellite observations can complement in situ measurements, although inversion models are needed to derive the wave period parameter. Hindcast and reanalysis databases have been derived from numerical wave simulations, which are validated against in situ and satellite observations. These databases allow for long-term assessments that capture the temporal variability of the wave resource. However, more detailed, and refined assessments of the wave energy spectrum are not possible given the use of integrated parameters, such as peak period *Tp* and significant wave height *Hs* (Guillou et al., 2020).

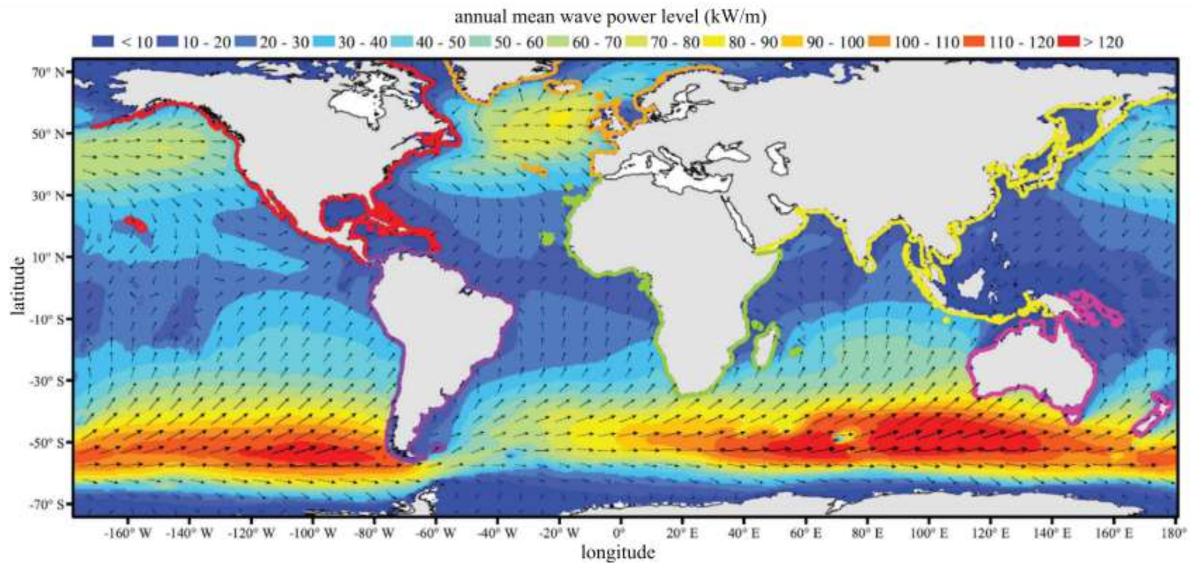

Figure 2.5 Global wave resource distribution
Source:(Gunn & Stock-Williams, 2012)

The wave energy resource is variable both spatially and temporally. Spatially on a global level, the wave power resource is evenly distributed between the Southern and Northern Hemispheres but is concentrated within 30-60 degrees of latitude, as seen in Figure 2.5. Nonetheless, spatial assessments of average wave conditions do not provide decision-makers or developers with sufficient information. The temporal variability of the wave resource ranges from seconds to decades. Short-term variability is characterized by direction, height, and period irregularity and it can happen in seconds or minutes, while medium-term variability is characterized by changes in sea states observable on an hourly or daily basis. In this term, wave power has high predictability, especially compared to other renewable resources, as the *Hs* can be accurately predicted in advance by a couple of days (Guo & Ringwood, 2021).

Long-term variation commonly refers to the inter-seasonal and inter-annual variability of the wave resource. Temporal wave resource assessments, long-term assessments with high temporal resolutions, are increasingly important as variability can have a significant influence on the energy exploitation and economic performance of a WEC device (Guo & Ringwood, 2021). In fact, climate change, and more specifically ocean warming, is changing the global wave climate, and an increase in wave power is expected in warmer oceans (Reguero et al., 2019).

To address the long-term variability of the wave spectrum, the technical specification by the International Electrotechnical Commission, recommends that a wave energy resource assessment should cover a minimum of ten years on a minimum temporal resolution of three hours. While the spatial resolution varies according to the stage of the project, reconnaissance, feasibility, or design stage (Guillou et al., 2020; IEC, 2014).

2.3.3 Wave Energy Converters

Wave energy converters (WEC) are devices that harvest the energy that is contained in ocean waves and generate electricity. In general, it can be conceptualized that WECs absorb either the kinetic energy as moving bodies, the potential energy through overtopping devices or attenuators, or both. WECs have not yet seen convergence towards a specific design as other mature renewable technologies such as wind, with over 1000 estimated device patents. According to Neill et al (2018), the technologies can mostly be grouped into one of five different types based on their working principles:

- Attenuator
- Oscillating wave surge converters (OWSCs)
- Oscillating water column (OWC)
- Overtopping devices
- Surface point absorber

Figure 2.6 summarizes the different WEC technologies.

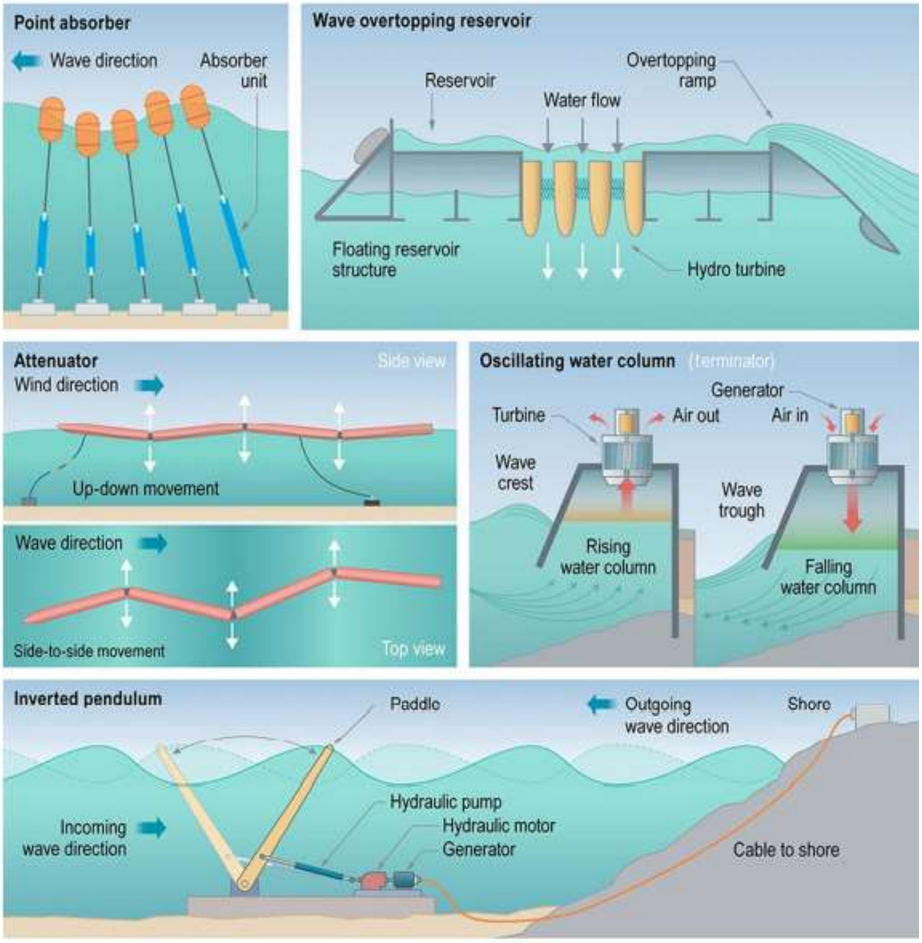

Figure 2.6 Overview of Wave Energy Converter Technologies
Source:(Neill & Hashemi, 2018)
Note: The "inverted pendulum" is commonly known as the Oscillating Wave Surge Converter

An attenuator is a long floating device commonly composed of multiple floating bodies connected by hinged joints aligned with the direction of wave propagation and captures the wave energy by constraining the movements along its length. The most recognizable attenuator is the *Pelamis* device.

OWSCs work as an inverted pendulum and are composed of an oscillating arm pivoted to the seabed and a paddle or collector (direction-dependent). The movement generates electricity through a hydraulic pump and motor. The *Oyster* device is an example of OWSC and benefits from the surge motion of waves in shallower waters (direction-dependent).

OWC devices are partially submerged, hollow structures with air trapped above the water column. Waves compress and decompress the air inside and channel it through a turbine to generate electricity. The *Pico* and *Limpet* are examples of OWC devices.

Overtopping devices capture water into a reservoir and release it back through turbines installed at the bottom of the reservoir. Overtopping devices are exemplified by the *Wave Dragon*, a floating device, and the *OBREC* device, a fixed prototype.

Lastly, Point Absorbers are floating structures similar to buoys that absorb wave energy from all directions (unidirectional). An example of a point absorber device is the *WaveBob*.

WECs still face relevant technical and non-technical challenges; WECs require specialized and reliable structures and power take-off systems to generate electricity, leading to high capital costs (CapEx); Because WECs operate in the offshore environment, they face high installation, operation, and maintenance costs (OpEx); Spatial and temporal variability, which are site dependent, can result in fit-for-purpose devices hampering convergence to an optimal design. These factors, among others, characterize wave energy with high uncertainty and risk, low maturity, and high capital requirements, which can discourage both private and public investments.

Furthermore, WEC survivability is another relevant challenge that wave energy development faces. WECs, especially those that operate on the surface, are exposed to extreme weather events. Storms and breaking waves can damage WECs. This is furthermore critical because usually where the theoretical resource is higher, also the probability of extreme events increases. WECs are designed to operate and convert energy under a range of conditions, usually the most frequent sea states, but not under these types of events. Ensuring WEC survivability under these types of events increases the capital and maintenance costs of the devices.

2.3.3.1 Power Matrix

The overview of wave resource assessment presented in section 2.3.2 refers to what is known as a “theoretical resource”. A theoretical resource assessment estimates the average energy available for a wave resource at a certain location based on numerical modeling.

On the other hand, the “technical resource” refers to the portion of the theoretical resource that can be captured by employing a specific WEC or technology in a potential location (Neill & Hashemi, 2018). Thus, to assess the technical resource, it is necessary to consider the device or technology characteristics, allowing for the estimation of the potential energy output. To approximate this technical resource, WEC power matrices (device characteristics) in combination with wave scatter diagrams (theoretical resource) are commonly employed.

Power matrices are the equivalent of power curves used for wind energy and showcase the potential power output of the device for a given sea state, characterized by significant wave height (*Hs*) and wave period (wave energy period *Te* or peak period *Tp*). An example of a wave power matrix used in this research for a generic 750kw farshore WEC device is shown in Figure 2.7. The combination of WECs power matrices and the wave scatter diagram, which provides the bivariate distribution of sea states occurrence among wave heights and periods, allows for the estimation potential energy output of a specific device. (Guillou et al., 2020; Guillou & Chapalain, 2018; Neill & Hashemi, 2018)

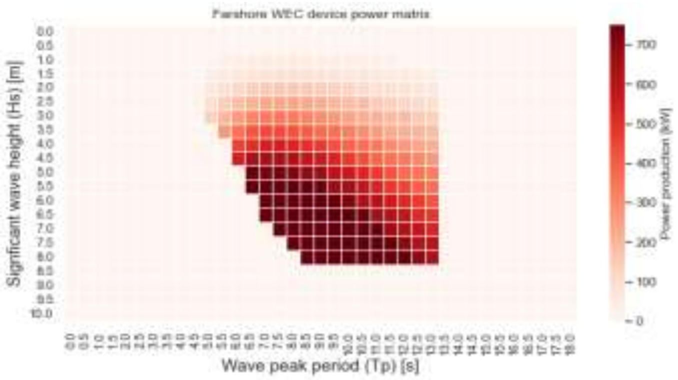

Figure 2.7 Farshore Wave Energy Converter 750kw Power Matrix. Range depth 50-150 m.

At more developed stages of a wave project, hydrodynamic modeling is employed to assess with greater precision the potential power output of specific WEC devices, at specific locations and with specific WEC farm arrays.

Ultimately the practical resource is the portion of the technical resource that is available after considering other technical, economic, social, and environmental factors. Excluding undesirable areas such as locations with low power density, marine protected areas, and remote locations without electricity infrastructure, among others.

2.3.4 Trends and development trajectories

2.3.4.1 Global overview

By 2020, only a combined active capacity of 2.3 MW of WECs was active in 9 projects across 8 countries and 33 devices (IRENA, 2020b). Nonetheless, from 2010 to 2021, 12.7 MW and 24.7 of cumulative installations were installed in Europe and at a global level, respectively, of which most have been decommissioned following mostly successful completion of testing programs (Ocean Energy Europe, 2022). Thus, the distribution of active projects is not representative of the global interest in the technology. In fact, the collaboration program on Ocean Energy Systems (OES), whose primary mission is to stimulate research, development, and deployment of Ocean Energy Systems, has 22 member countries plus the European commission as of December 2021 (IEA-OES, 2022).

Almost all OES member countries have enacted policies to support and advance ocean energy at varying degrees of scope, focusing on strategic roadmaps for innovation, regulatory R, and governmental support. Examples include France’s introduction of the contribution of ocean energy into its “Energy Pathways 2050” study (IEA-OES, 2022; RTE, 2021).

The European Commission, through its Offshore Renewable Energy Strategy, foresees implementing 100 MW pilot farm projects by 2025 to reach commercial size by 2030. Spain published a roadmap to reach 40-60 MW of wave energy by 2030 (IEA-OES, 2022). Furthermore, The UK has historically deployed the greatest number of projects, even if by 2020 no devices where active, it has several projects lined up in the near future. Figure 2.8 showcases locations where wave energy projects are projected. It is estimated that up to 2.8 MW of wave energy capacity is lined up for deployment in Europe, and 1.1 additional MW in the rest of the world (Ocean Energy Europe, 2022).

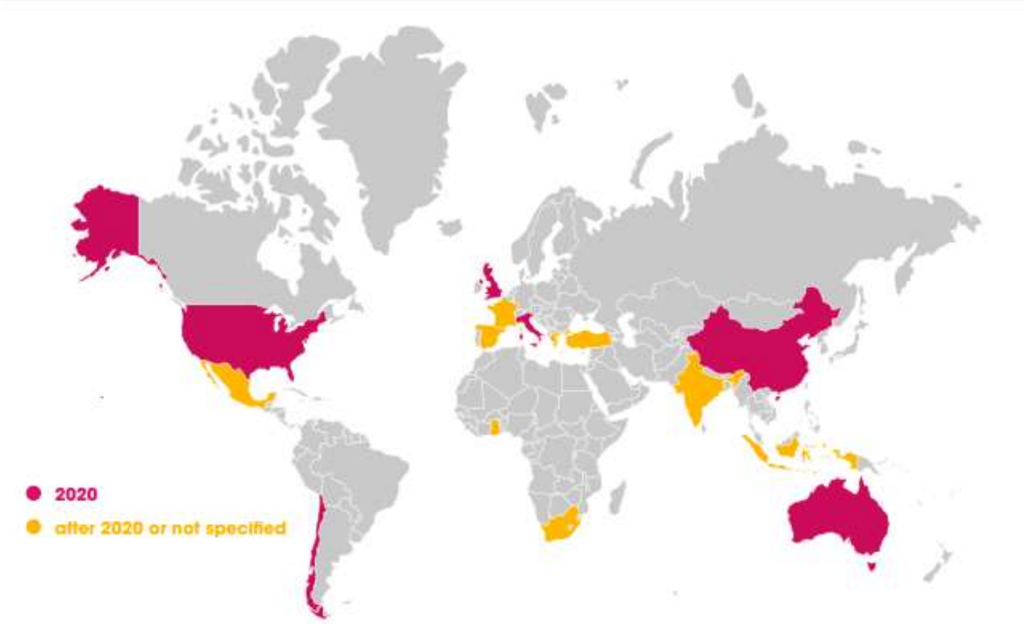

Figure 2.8 Global distribution of active and projected wave energy projects by 2020
Source: (IRENA, 2020b)

Even if the first patent published in France for a wave energy device was in 1799, wave energy technology is still considered to be in its infancy, as there are no fully commercial-scale wave energy projects in operation. This can be mainly attributed to the fact that WEC technologies have not yet demonstrated to harvest enough wave energy at a low enough cost for commercial purposes. Further highlighted by the fact that there's currently no dominant design in wave energy.

Technology Readiness Level (TRL) is a system developed by NASA to estimate the maturity of innovative technologies. TRL is commonly used to discuss the technical maturity of different types of technologies on a consistent and uniform basis. TRL proposes a list of milestones and is based on a scale of 1 to 9, being 9 representing the most mature technology. This system provides a useful framework to assess the development of wave energy technology. Furthermore, within the context of ocean renewable technologies, the OES proposed a division of the development process into stages founded on the TRL levels. Table 2.1 provides and overview of TRL and development stages.

Table 2.1 Characteristics of TRLs and development stages
Note: Adapted from [1](Guo & Ringwood, 2021) and [2](Hodges J. et al., 2021)

TRL	Description[1]	Development Stages[2]
1	Basic principles observed and reported	**Stage 0**: Concept Creation
2	Technology concept formulated	**Stage 1**: Concept development
3	Analytical/ experimental key function proof-of-concept	
4	Technology component and/or basic technology subsystem validation in a laboratory environment	**Stage 2**: Design Optimization
5	Technology component and/or basic technology subsystem validation in a relevant environment	**Stage 3**: Scaled Demonstration
6	Technology system prototype demonstration in a relevant environment	

7	Technology system prototype demonstration in an operational environment	**Stage 4**: Commercial-scale single-device demonstration
8	Actual product completed and qualified through test and demonstration	
9	Operational performance and reliability demonstrated for an array of types of machines	**Stage 5**: Commercial-scale array demonstration

Wave energy devices, due to the various designs and operation principles, find themselves at different TRLs. The Joint Research Center (JRC) of the European Commission considers that most current wave energy deployments are undergoing testing at TRL7, with only OWC devices having achieved TRL8. Current devices have shown the capability to survive wave loadings at high waves, but that long-term reliability is not fully proven. Furthermore, there still exists limited information on electricity generation to validate the progress of WECs at higher TRLs. Under the OES development stages, this would place the technology on the commercial-scale single-device demonstration stage. In contrast, the TRL levels of wave energy devices are lower than that of Tidal energy, for which the TRL of a Horizontal axis turbine is set at 8 (Magagna, 2019). An overview of the TRL of different wave energy devices is presented in Table 2.2.

Table 2.2 TRL of wave energy devices
Source: Ocean Energy: Technology Development Report by the Joint Research center of the European Commission (Magagna, 2019)

Device Class	Highest TRL achieved
Attenuator	7
Point Absorber	7
OWSC	7
OWC	8
Overtopping	5
Other	3-7

Even if WEC devices are still in the demonstration phase, this is the closest the technology and sector have been to commercialization. Because of these, developers are intensifying their activities. They are finding ways to increase the power output of the devices, envisioning utility-scale windfarms, as well as identifying suitable business plans to enter the market. In addition, developers are also considering fit-for-purpose devices designed for niche markets such as aquaculture farms and oil & gas offshore projects.

On the other hand, technology readiness is just one of the factors relevant to the commercialization and large-scale deployment of wave energy. Devices must also be able to provide affordable electricity for utility markets or a reliable supply for niche markets. The Levelized Cost of Electricity (LCOE) is a common measure to compare different methods of electricity generation. LCOE essentially evaluates the net present value of the economic cost of an electricity generation method over its lifetime. If the LCOE of wave energy is not competitive against other renewable technologies, commercialization of wave energy devices may fail. Furthermore, WEC survivability remains one of the key concerns, as several WEC pilot projects have failed due to storms.

Because of this, the cost of energy of wave can also be a good indicator of the development of the technology. The Joint Research Center of the European Union (JRC) estimated that the LCOE of wave energy, with 8 MW installed at the time, was at an average of 560 EUR/MWh (Magagna, 2019). While the OES considers the current LCOE of commercial stage wave energy to be around 120-470 $/MWh (100-400€/MWh) (OES, 2015). While recent studies indicate that if proper site matching occurs LCOE can be as low as 70$/MWh (Lavidas, 2018). The range can be attributed to the different technologies, but also the resource available at the site. Because if this it is expected that different wave energy projects will have different LCOEs depending on their location.

Because the wave energy resource is still untapped and the technology is still considered in its developing, it is expected that there is high-cost reduction potential in the future, especially as learning experiences accumulate. As stated in de declaration of intent of The European Strategic Energy Technology Plan (SET Plan) to boost the transition towards climate-neutral energy systems, the average LCOE of wave energy should be reduced to 200 EUR/MWh by 2025, 150 EUR/MWh by 2030, and 100 EUR /MWh by 2035 (SET Plan Secretariat, 2016). Nevertheless, as shown in Figure 2.9, some developers indicate that the cost could even drop earlier than these targets.

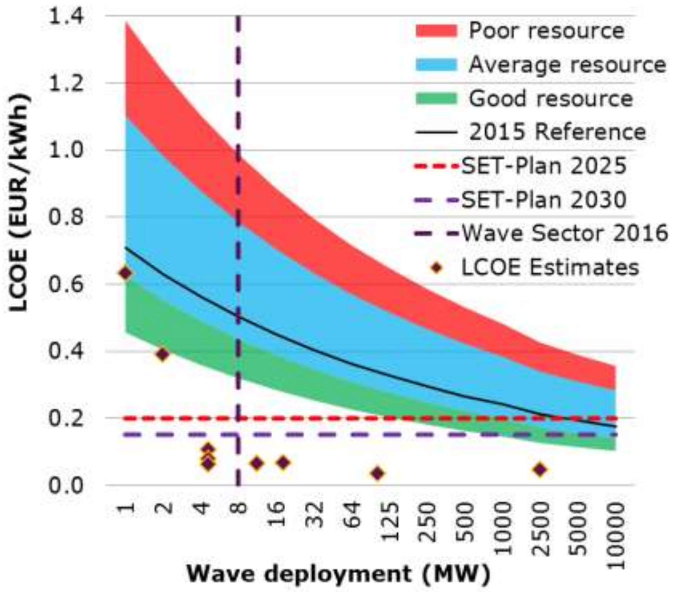

Figure 2.9 LCOE predictions for wave energy
Source: Ocean Energy: Technology Development Report by the Joint Research center of the European Commission (Magagna, 2019)

Ultimately, the development of wave energy still faces technical, economical, and administrative challenges. Furthermore, uncertainty remains about whether it will achieve commercial stage in the short and medium term. The rapid rise of other renewables, including ocean renewables like offshore wind and tidal, also represents a commercial challenge, as they have demonstrated higher levels of technology readiness as well as demonstrated commercial application.

Furthermore, solar and wind, have many years of expertise and are currently only addressing incremental technical problems. Regulatory, legislative, and technical synergies could be found with the offshore wind sector to further increase the competitiveness of wave energy but this is dependent on site location. Public and government sectors need to play an important role, alongside academia and researchers, to develop and implement national strategies to achieve carbon-neutral electricity systems. Wave energy, without a doubt, has an enormous potential to assist in these targets but remains unattractive to investors as it is still considered a costly and risky venture.

2.4 Electrical Grid Systems & Power System Planning Fundamentals

2.4.1 Background

The electric power system is nowadays one of the man-made largest scale systems. It comprises an astounding number of components and interconnections, ranging from household electric appliances to large nuclear generators. Planning, installing, operating, and expanding this system is no trivial task and involves a great number of different actors and industries, including among others, government agencies, consumers, private and public owned, generators, specialized contractors, etc.

Over the last decades, the power industry in most parts of the world has moved towards a market-oriented environment in which electric power is treated as a commodity. This market approach implies that the generation, transmission, and distribution belong to different entities or actors. The planner and operator of the network do not necessarily decide where generators must be installed, but rather the decision can be made by private companies constrained by economic and regulatory constraints and involving various other stakeholders.

Furthermore, the push toward the decarbonization of the power system has further changed the dynamics of power system planning. High-share renewable power systems are characterized by electricity supply dependent on variable weather conditions and the type of technology. The spatial and temporal availability of variable resources such as wind, solar, and waves are a key factor for generator dispatch, storage, and transmission needs, and grid congestion of the high share renewable electricity system as well. (F. Neumann et al., 2020). In essence, power system planning is the process in which the aim is to decide on new as well as upgrading existing system elements, to satisfy the loads foreseen in the future. The main system elements considered in power system planning are the Generation facilities, Transmission lines, Substations, and Capacitors/Reactors.

Common decisions include where to allocate the elements, when to install them, and the selection of the element specifications. In this exercise, satisfying the expected load is critical. Power system planning is complex given the numerous interactions of the components, such as the network, loads, generators, storage, and different energy carriers. Furthermore, the power system must allow for the load to be met while staying within the constraints imposed by the different components of the system. (Seifi & Sepasian, 2011). Within power system planning, one can further specify the planning problem depending on the component. Generation Expansion Planning (GEP), Transmission Expansion Planning (TEP), Substation Expansion Planning (SEP) and Network Expansion Planning (NEP) are common names for specific expansion planning studies and methodologies focusing on specific areas of the power system.

Power system planning problems, although not always in practice, are carried out through mathematical optimization techniques and the use of models or modeling tools. These mathematical optimization techniques are defined by an objective function and a set of decision variables that are subject to a set of constraints. Decision variables are the independent variables. In other words, these variables are determined by the modeler or decision maker and dependent variables are determined based on them.

An example of a decision variable can be the fuel prices, while a dependent can be the CO_2 emissions of the burning of those fuels. Constraints define and divide the solution space of the optimization problem. The constraints seek to represent the technical, environmental, and economic limitations of the real world within the optimization problem. The set of solutions of the mathematical optimization problem that comply with the set of constraints is known as the feasible region. Within the feasible region, the modeler or decision maker should select the most desirable decision. The objective function is a mathematical function in terms of the decision variables which represents the objective or the desirable solution. For power systems planning, the objective is usually to minimize time-discounted investment and operation costs of the system expansion, but can also be to minimize system losses, among others. Multi-objective optimization problems refer to problems in which multiple objective functions are to be simultaneously optimized. A generic optimization problem model is presented below, where x is the decision variable, $C(x)$ is the objective function, which in this case seeks to minimize, and the optimization is subject to the constraint $f(x)$ and $g(x)$. (Seifi & Sepasian, 2011)

$$\begin{gathered} \min_{x} C(x) \\ s.t. \qquad f(x) = 0 \ \text{ and } \quad g(x) >= 0 \end{gathered} \tag{2.8}$$

2.4.2 Solving Optimization problems

Various techniques exist to solve optimization problems and are generally classified as mathematical and heuristic methods. Mathematical optimization techniques formulate the problem in a mathematical representation as the problem formulation above. Depending on the properties and characteristics of the problem formulation different designations are employed. If the objective function and constraints are not linear, the problem is designated as a Non-linear Optimization problem (NLP). If the objective functions and constraints are linear, the problem is categorized as a Linear Programming (LP) optimization problem. While most mathematical-based algorithms can guarantee to reach an optimal solution, it does not necessarily guarantee reaching the global optimum, with the exception of LP. (Seifi & Sepasian, 2011)

On the other hand, Heuristics algorithms are less restricted requirements and many of them are inspired by biological behaviors or physical phenomena. They are commonly employed for optimization problems that may not be possible to express in strict forms of mathematical-based algorithms. Heuristic algorithms may not guarantee optimality, but they seek good solutions or local optima. In essence, the algorithm starts with an initial set of solutions, and these are modified by different methods, such as selection, mutation, recombination, crossover, etc. The best among these modified solutions is selected and the process repeats itself until an optimum is found, either local or global. Genetic or evolutionary algorithms are inspired by genes and evolutionary strategy, Particle Swarm algorithms are inspired by the behavior of banks of fishes, flocks of birds, or swarms, Tabu Search is based on human memory and Ant Colony is based on the behavior of ants.(Seifi & Sepasian, 2011)

Specialized software has been generated based on different mathematical and heuristic algorithms and is commonly used to solve optimization problems. Notable open-source solvers exist such as CBC and GLPK, however, the enormous amount of computational power needed to resolve the European power system with its hundreds of nodes and thousands of components leads to the need for commercial solvers such as Gurobi.

2.4.3 Existing High-share renewable power system models and Selection of model

Over the last decades, many models have been developed to assess and evaluate energy and electricity systems, in particular, to better understand and address the challenges related to variable renewable energy system integration. From short-term operation to long-term investment and planning, models have been used to assess the technical feasibility, economic viability, and potential of High share renewable energy and electricity systems. They have been further used to identify potential transition and decarbonization pathways, and to identify and provide insights on the necessary steps to decarbonize our energy systems. Energy system models can be categorized according to their purpose, although they are not necessarily exclusive. Power System analysis tools are used to study the dynamics between the components of a power system. Operation Decision Support models are tools developed specifically to simulate and optimize the operation and dispatch of the system, while Investment Decision Support models optimize the future investments of the energy system. Lastly, Scenario tools are employed to investigate future-long term scenarios of the studied sector. Energy models can also be differentiated by their approach; either a top-down or a bottom-up approach. Top-down models are based on macroeconomic relationships and long-term changes, while bottom-up models are based on descriptions of the technological components of the energy system. They can further be differentiated by their methodology, mainly divided into three categories: simulation, optimization, and equilibrium models. Simulation models generally follow a bottom-up and simulate an energy system based on detailed equations and characteristics of the components. They are useful for scenario analysis and testing of the system topologies and components. Meanwhile, optimization models seek to optimize a given aspect of the system, which in most cases is related to investment planning and system operation. As was discussed in the previous section, there are multiple optimization approaches, e.g. linear programming. Lastly, equilibrium models use an economic approach, used to study how the energy sector related to the rest of the economy. They are used to evaluate the impact of policies across the economy as a whole. (Ringkjøb et al., 2018)

Given that the focus of the thesis is to assess the potential impact of wave energy integration on the European Transmission network (electricity sector only), different requirements for an energy system model where desired. A power system analysis tool with operation decision support on an hourly basis was deemed necessary to assess the interactions between the components of the network, storage technologies, competing variable renewables, and wave energy. Furthermore, since the scope of the research is on future high-share renewable power systems, investment decision support was desirable to assess factors that influence the penetration of wave energy under optimal configurations of the system. Moreover, given the geographical scope of the research, it is necessary to leverage on existing research and studies that had already modelled the European transmission grid. And lastly, given the need to add the wave energy resource, well-documented open-source models have a strong preference.

PyPSA-Eur was selected and modified to perform this research. It is a dataset and optimization model specific for the European power system at the transmission network level modelled on the Power System Analysis (PyPSA) toolbox (T. Brown et al., 2018; Hörsch et al., 2018a). It is suitable for both operational and investment planning studies. Furthermore, and of great importance, it has resource assessment capabilities for solar and wind, for which many of the functions can be adapted for wave. In addition, its open-source nature allows it to be modified and improved by different research groups as novel data, methodologies or technologies become available. A thorough description of the model is provided in the following section

2.4.4 PYPSA-Eur

A critical part of this study was the development and integration of representative WECs in the existing dynamic energy system model, PyPSA-Eur, an open-source model dataset and optimization specific for the European power system at the transmission network level which covers the whole European Network of Transmission System Operators for Electricity (ENTSO-e) area (Hörsch et al., 2018a). The model is built on top of the Python for Power System Analysis (PyPSA) software, "an open software toolbox for simulating and optimizing modern electrical power systems over multiple periods" (T. Brown et al., 2018).

PyPSA-Eur and its dataset include models, assumptions for conventional generators, renewable generators, storage units, and network and transmission lines. It is suitable for both operational studies and generation and transmission expansion planning studies. PyPSA accommodates different renewables, such as solar photovoltaic, wind turbines, and solar thermal collectors, among other renewables. For the first time, a Wave Energy Converter (WEC) was integrated into PyPSA, enabling to assess the impact of wave energy on the European Energy Grid. (*PyPSA-Eur Documentation*, 2022)

2.4.4.1 Network Topology: European power System (ENTSO-E)

As mentioned above, PyPSA-Eur is an open-source model specific for the European power system at the transmission network level which covers the whole European Network of Transmission System Operators for Electricity (ENTSO-e). The network topology of the European transmission is retrieved from the ENTSO-E grid map (ENTSO-E, 2022b) with an extended version of the Gridkit toolkit (Wiegmans, 2016). The topology and dataset include all High Voltage Alternating Currents (HVAC) lines above 220 kV and all high voltage direct current (HVDC) lines. The topology of the model can be seen in Figure 2.10. In total, the modeled network includes approximately 6600 HVAC lines, 3000 substations, and 70 HVDC lines across the different zones of the ENTSO-E area. The topology excludes north-African countries and Turkey, which are interconnected to the European grid. Interconnections to Russia, Ukraine, and Belarus, as well as small island states such as Crete, Cyprus, and Malta, are also excluded. (Hörsch et al., 2018a; M. S. F. Neumann et al., 2021).

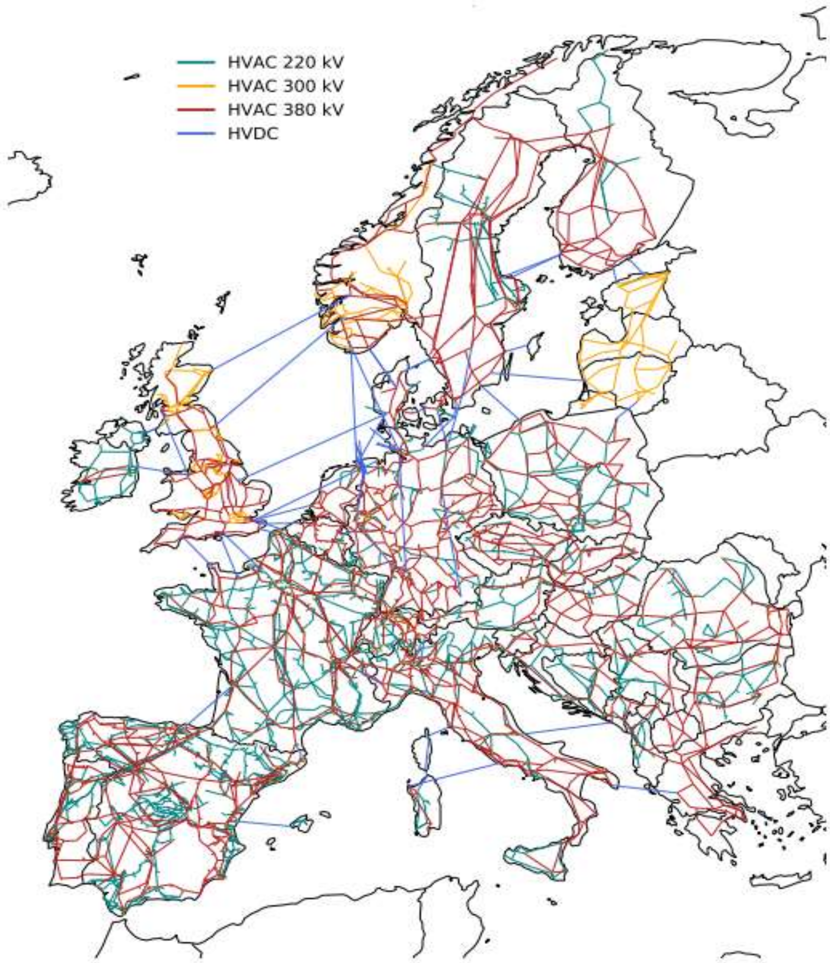

Figure 2.10 European transmission network topology in PyPSA-Eur
Source: (M. S. F. Neumann et al., 2021)

The electrical parameters for the modeled transmission lines are based on standard AC line types shown in Table 2.3. Furthermore, to approximate N -1 security criterion, the line loading of HVAC lines is restricted to 70% of their nominal rating. This criterion represents the requirement for system redundancy and allows for the system to continue operation if one line or component were to fail (Hörsch et al., 2018a; M. S. F. Neumann et al., 2021).

Table 2.3 Standard line types and parameters for AC lines in Pypsa-Eur
Source: (Hörsch et al., 2018a)

Voltage level (kV)	Wires	Series resist. (Ω/km)	Series ind. Reactance (Ω/km)	Shunt capacity (nF/km)	Current therm. limit (A)	App. Power therm. Limit (MVA)
220	2	0.06	0.301	12.5	1290	492
300	3	0.04	0.265	13.2	1935	1005
380	4	0.03	0.246	13.8	2580	1698

The model employs Voronoi cells as geographical catchment areas and each of these cells is associated with one substation. These Voronoi cells determine the region that is closer to a certain substation than to any other substation within a country's borders. These cells are used to link electricity loads, power plant capacities, renewable resource potentials, and determine the feed-in potential by potential renewable generation. It is assumed in the model that supply and demand always connect to the closest substation of the transmission network and ignores any constraints at the low-voltage distribution level. Figure 2.11 showcases the geographical onshore Voronoi cells within the European transmission network. Similar Voronoi cells are created for offshore generation potential.

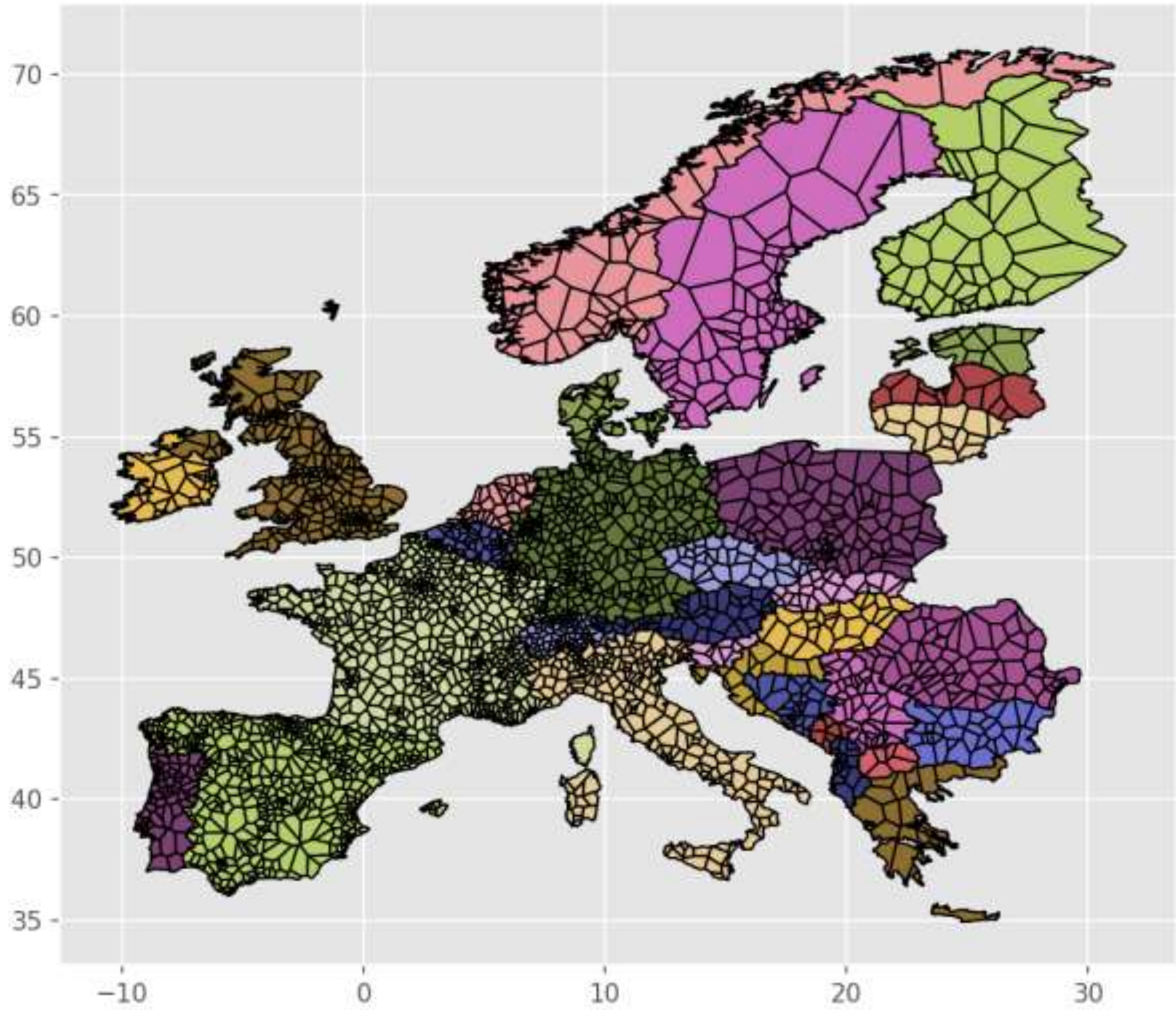

Figure 2.11 Exemplary Onshore Voronoi cells of the PyPSA-Eur European transmission network

In addition, PyPSA-Eur also has available a dataset of operational conventional power plants. The dataset was obtained by the developers through the power-plant matching tool which incorporates multiple power-plant databases (Hörsch et al., 2018a). The dataset includes data on technology, capacity, fuel type, age, and location for multiple power plants including oil, combined cycle gas turbine (CCGT), open cycle gas turbine (OCGT), hard coal, lignite, nuclear, biomass, and geothermal generators.

The dataset also includes existing hydro-electric dams, run of the river, and pumped-hydro storage plants (M. S. F. Neumann et al., 2021). Because this research is focused on 100% renewable scenarios, this dataset is only used partially, only using the conventional geothermal plants and the existing hydro-electric, pumped-hydro, and run-of-river plants. Within the execution of the model, these plants are not considered extendable. For more information on the power plant dataset and hydro-electric generation consult (Hörsch et al., 2018a)

Regarding other existing renewable generators, the model disregards existing wind and solar capacities and deploys them from scratch. Existing storage technologies are also not considered and are also installed and extended during the model's execution. Two different storage technologies are considered: Battery storage and hydrogen storage. Battery storage represents short-term storage with an energy-to-power ratio of 6 hours, used to balance variability on a day-to-day basis. Hydrogen storage is the long-term option for balancing yearly or seasonal variabilities. Hydrogen storage is modeled on a combination of electrolyzers, storage in steel tanks, and fuel cells to convert electricity (M. S. F. Neumann et al., 2021).

2.4.4.2 Renewable Energy Potentials and Available Land

As mentioned above, the PyPSA-Eur model can derive the renewable energy potentials and generation availability time series for different renewables, such as solar photovoltaic, wind turbines, and solar thermal collectors, among other renewables. One of the objectives of this research was to expand the renewable energy capabilities of the model to include wave energy convertors.

The geographical areas eligible for the development of renewable technologies in the model are calculated for each Voronoi cell and each technology. The land eligibility of the different renewable energy technologies that can be built within a certain region is constrained by the following factors; eligible codes of the CORINE land use database (Copernicus, 2022); constraints on natural protection areas in the Natura 2000 dataset (European Commission, 2022a); and water depth from the GEBCO bathymetry dataset and distance from shore constraints for offshore technologies.

Once the eligible areas have been determined, the model expresses the installable renewable capacity potentials based on the available land, and by the packing rate or capacity per square kilometer for each technology. The default packing rates of solar and wind in the model are a fraction of the technical packing rate to account for other factors such as social acceptance, political willingness, and regulation. (Hofmann et al., 2021; M. S. F. Neumann et al., 2021)

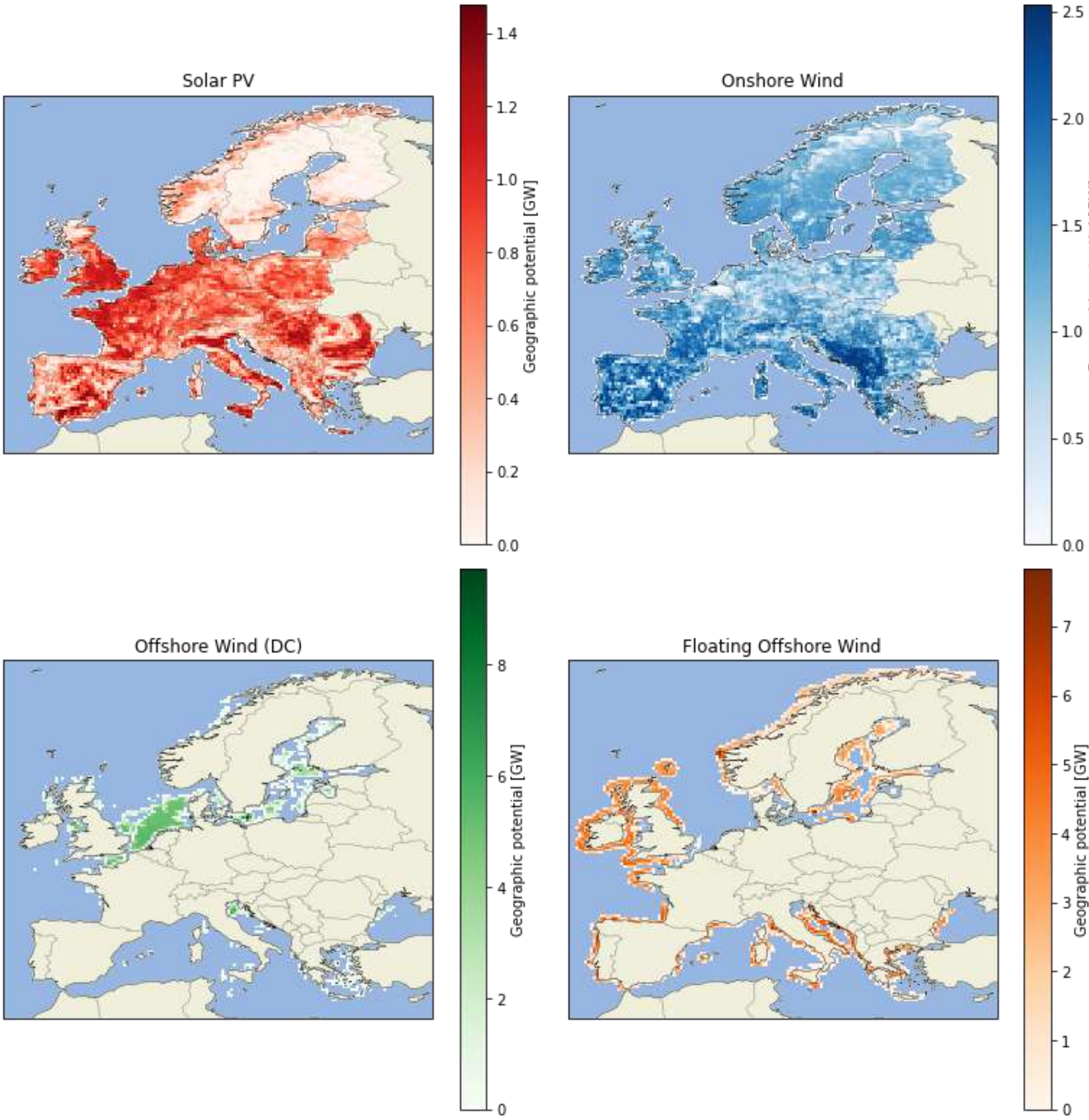

Figure 2.12 Exemplary capacity potential [MW] of renewable technologies in PyPSA-Eur
Source:(*PyPSA-Eur Documentation*, 2022)

2.4.4.3 Electricity Demand

Data on electricity consumption is obtained from historical data. The electricity demand profiles from each country in the network were taken from the ENTSO-E consumption database(ENTSO-E, 2022a). In order to heuristically allocate the load time series on a country level to the Voronoi substations, the load is distributed by 60% by gross domestic product (GDP) and 40% by population density within the Voronoi. Population density serves as a proxy for residential demand while GDP is used as a proxy for industrial demand(Hörsch et al., 2018a; M. S. F. Neumann et al., 2021).

2.4.4.4 Network Simplification

Because modeling the entire European transmission system in full detail and resolution is a complex task and requires high computational power to be solved in a reasonable time, the model allows for simplifying the network topology lowering the spatial and temporal resolution. These reduction algorithms are implemented in PyPSA software, the foundation of the PyPSA-Eur model.

Spatially, the model initially transforms the network into a uniform voltage level and aggregates nodes with only one edge or "dead ends" to neighboring nodes in an iterative process, also connecting resources to these adjacent nodes. Subsequently, the network is further reduced by employing a k-means network clustering algorithm, which weighs the remaining buses according to their regional electricity consumption creating a new bus that represents the set of clustered nodes (Hörsch & Brown, 2017). All generators, storage units, and loads are aggregated by their technology type at the bus. The maximum expansion potential of generators are also aggregated and the availability-time series is averaged by weighting. The level of aggregation is chosen by the user and can be anything between the number of original nodes in the European power network to one node per country. (Hörsch et al., 2018a; Hörsch & Brown, 2017; M. S. F. Neumann et al., 2021)

Temporally, the model allows the user to select the temporal resolution of the model. These simplifications provide flexibility to the model depending on feasible resolution times and computational power.

3. Methods and Model Formulation

This chapter presents in greater detail the components, parameters, assumptions, and methods developed and employed for this research. An in-depth description of the conceptualization, development, and implementation of the novel wave energy converter subroutines into the existing PyPSA-Eur model is presented, as well as the configuration and set up of the model for analysis.

This research was performed under the direct supervision of the Marine Renewable Energies Lab at the Offshore Engineering Group at TU Delft, led by Dr. George Lavidas. This position provided the research with significant expert knowledge on marine renewable energy, relevant insights for the integration of wave energy converters, as well as necessary tools and equipment to perform the energy system model.

At the heart of this research was the development and integration of representative models for wave energy converters into the existing dynamic energy system software PyPSA, so they can ultimately be employed within the PyPSA-Eur model. PyPSA-Eur being the PyPSA model and dataset-specific of the European power system at the transmission network level, covering the whole European Network Of Transmission System Operators for Electricity (ENTSO-e) area (Hörsch et al., 2018b). In brief, the PyPSA-Eur model serves as a model for investment and operational optimization of the European energy system.

Therefore, one of the main objectives and initial step of this research was to expand the renewable energy capabilities and database of the model with new ocean energy converters subroutines and with real high-resolution ocean climate data. To achieve this, the project leveraged and was founded on the existing conversion models for wind and solar technologies within the PyPSA model, especially on the scripts related to the selection process for the optimal deployment of renewable energy. In addition, and similarly to the existing resource assessments of solar and wind within the model, the addition of wave energy convertors employed the ERA5 reanalysis dataset by the European Centre for Medium-Range Weather Forecasts (ECMWF) which contains global climate and weather data for the past 4-7 decades (Hersbach et al., 2020).

Once the renewable capabilities of the model were expanded to include the wave energy resource and wave energy converters, the research focused on performing a set of power system optimization scenarios of the European transmission grid in a greenfield approach of a 100% renewable power system under 2018 weather conditions. Co-optimizing for the first-time wave energy capacities with solar PV, onshore and offshore wind, in combination with battery storage, hydrogen storage, and European transmission infrastructure, and subject to the geographic potentials and Spatio-temporal capacity factors of these technologies.

3.1 Problem Formulation

In brief, PyPSA-Eur is based on the PyPSA software which is an investment and operational optimization model of the European power network which minimizes total annual system costs considering the variable and fixed costs of generation, storage, and transmission given a set of technical and physical constraints expressed mathematically. It is a partial equilibrium model that can optimize both short-term operation and long-term investment of the European power system as a linear problem, employing the linear power flow equations. (T. Brown et al., 2018)

The objective function is

$$\min_{G,H,F,g}\left[\sum_{i,r} c_{i,r}\cdot\ G_{i,r}+\sum_{i,s} c_{i,s}\cdot\ H_{i,s}\ +\sum_{\ell} c_{\ell}\cdot\ P_{\ell}\right.$$
$$\left.+\sum_{t} w_t\left[\sum_{i,r} o_{i,r,t}\cdot\ g_{i,r,t}+\sum_{i,r} o_{i,r,t}\cdot\ h_{i,r,t}\right]\right] \tag{3.1}$$

Which consists of the generator capacity $G_{i,r}$ and their associated annualized costs for investments $c_{i,r}$ in node or location i for technology r, the storage power rating $H_{i,s}$ of storage technology s, and transmission line capacities P_{ℓ} for each line ℓ, as well as the dispatch of generators $g_{i,r,t}$ and storage units $h_{i,r,t}$ at time t and their associated variable and operational costs $o_{i,r,t}$ weighted by the period w_t such that the total duration adds up to one year.

To annualize the investment costs, the model employs an annuity factor A_c in the form of

$$A_c=\frac{1-(1+\tau)^n}{\tau} \tag{3.2}$$

Which converts the upfront investment of assets to annual payments in their net present value taking into account the lifetime n and the discount rate or cost of capital τ.

The dispatch of generators $g_{i,r,t}$ is constrained by their capacities $G_{i,r}$ and, particular to renewable generators, the availability of variable renewable derived from weather data expressed as a time and location-dependent availability factor $\bar{g}_{i,r,t}$ and a set lower bound for the dispatch $\ddot{g}_{i,r,t}$.

$$\text{s.t}\quad \ddot{g}_{i,r,t}\cdot G_{i,r}\quad\leq\quad g_{i,r,t}\quad\leq\quad \bar{g}_{i,r,t}\cdot G_{i,r}\qquad \forall i,r,t \tag{3.3}$$

Similarly, the dispatch of storage units is constrained by a similar equation

$$\text{s.t}\quad \ddot{h}_{i,s,t}\cdot H_{i,s}\quad\leq\quad g_{i,r,t}\quad\leq\quad \bar{h}_{i,s,t}\cdot H_{i,s}\qquad \forall i,s,t \tag{3.4}$$

With $\ddot{h}_{i,s,t}$ as negative, as the dispatch of storage can be positive when discharging and negative when absorbing power from the gird. Furthermore, because the energy levels $e_{i,s,t}$ of storage units have to be consistent and are limited by the energy capacity $E_{i,s}$

$$\text{s.t}\quad e_{i,s,t}=\eta_{i,s,0}^{w_t}e_{n,s,t-1}+\ w_t\cdot\ h_{i,s,t}^{inflow}-\ w_t\cdot\ h_{i,s,t}^{spillage}+\eta_{i,s,+}\cdot w_t\cdot h_{i,s,t}^{+}-\ \eta_{i,s,-}^{-1}\cdot w_t\cdot h_{i,s,t}^{-}\qquad \forall i,s,t \tag{3.5}$$
$$0\ \leq\ e_{i,s,t}\ \leq\ E_{i,s}$$

Where storage units can have a standing loss $\eta_{i,s,0}$, a charging efficiency $\eta_{i,s,+}$, a discharging efficiency $\eta_{i,s,-}$, natural inflow $h_{i,s,t}^{inflow}$ and spillage $h_{i,s,t}^{spillage}$.

Furthermore, the capacities of generation, storage, and transmission components are constrained by their maximum installable potentials as a ceiling and the existing components as a bottom constraint.

$$\text{s.t} \quad \ddot{G}_{i,r} \leq G_{i,r,t} \leq \bar{G}_{i,r} \qquad \forall i,r \qquad (3.6)$$

$$\text{s.t} \quad \ddot{H}_{i,r} \leq H \leq \bar{H}_{i,r} \qquad \forall i,s \qquad (3.7)$$

$$\text{s.t} \quad \ddot{P}_{\ell} \leq P_{\ell} \leq \bar{P}_{\ell} \qquad \forall \ell \qquad (3.8)$$

Crucially, Kirchoff's Current Law (KCL) requires that the inelastic demand for electricity $d_{i,t}$ at each bus must be met at each time t by either local generators or storage or by flows from branches

$$\text{s.t} \quad \sum_r g_{i,r,t} + \sum_s (h^{-}_{i,s,t} - h^{+}_{i,s,t}) + \sum_{\ell} K_{i\ell} P_{\ell,t} = d_{i,t} \qquad \forall i,t \qquad (3.9)$$

where $K_{i\ell}$ is the incidence matrix of the network.

The power flows $p_{\ell,t}$ are also constrained by the line capacities.

$$\text{s.t} \quad |p_{\ell,t}| \leq \bar{p}_{\ell} P_{\ell} \qquad \forall \ell,t \qquad (3.10)$$

Where $\bar{p}_{\ell}$ acts as an additional per unit security margin on the line capacity to comply with the N-1 criterion. These capacities can be optimized, but no new lines are considered.

To guarantee the physicality of the network flows, in addition to KCL, Kirchoff's Current Law (KVL) must also be enforced and imposes further constraints. KVL states that the voltage differences around any closed cycle in the network must sum to zero. KVL can be written as below. Each independent cycle c is expressed as a directed combination of lines ℓ by a matrix $C_{\ell c}$

$$\text{s.t} \quad \sum_{\ell} C_{\ell c} \cdot x_{\ell} \cdot f_{\ell,t} = 0 \qquad \forall c,t \qquad (3.11)$$

Where x_{ℓ} is the series inductive reactance of line ℓ. (T. Brown et al., 2018; Hörsch & Brown, 2017; M. S. F. Neumann et al., 2021)

A solved model provides optimized locations of generation, storage, and transmission capacities as well as the optimal dispatch of the components. The model also provides the levels of congestion of the network, levels of curtailment, and nodal electricity prices. Figure 3.1 presents a general overview of the PyPSA-Eur model, displaying visually the model inputs, outputs, constraints, and decision variables. The overview highlights the novel addition of wave energy, described in the following section. .

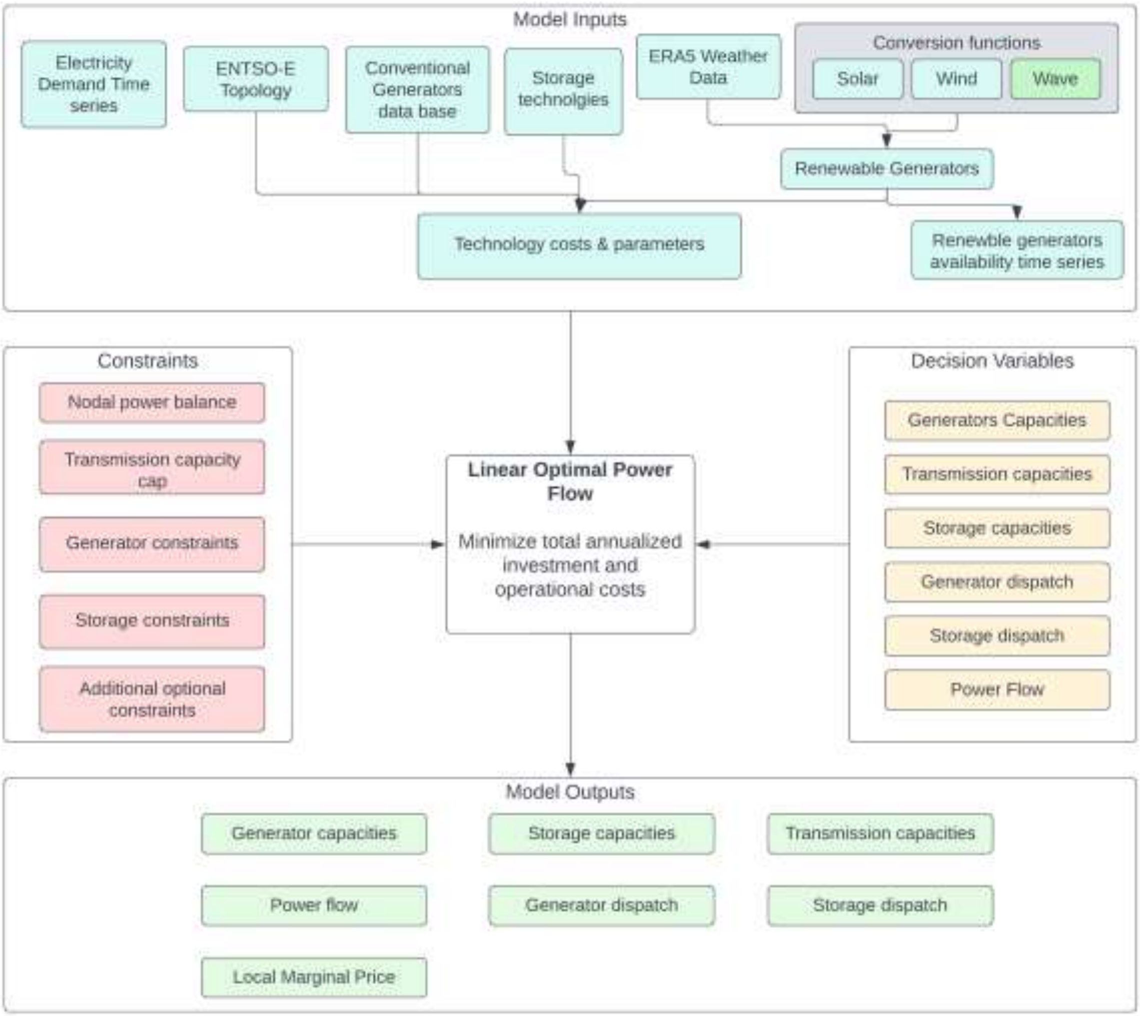

Figure 3.1 Model Overview

3.2 Conceptualization and Integration of Wave Energy Converters

Within the PyPSA model, the atlite module is the python package that allows for the estimation of the renewable power potentials and availability time series, originally only for solar and wind. To accomplish this, the model creates a container for a spatio-temporal subset of one or more topology and weather datasets and creates a NetCDF file under which data from different weather datasets can be laid. Once the weather data is gathered, a set of conversion functions can be called to derive power systems data, such as availability time series and the static potentials of renewable resources.

The python package already included the ability to download and gather ECMWF Reanalysis ERA5 data. This dataset provides various weather-related variables in an hourly resolution from 1950 onward on a spatial grid with a 0.25° x 0.25° resolution, most of which is reanalysis data. Thus, to assess the wave power potential within the model, two additional variables from the ERA5 dataset where included: Significant height of combined wind waves and swell (H_s) and Peak wave period (T_p). These two variables allow for the characterization of a given sea state, and in combination with a WEC power matrix, are used to estimate the power output of a device per sea state at each grid cell and time step.

For this research, three different WECs were integrated into the model; a Farshore 750kW device which operates on depths below sea level ranging from 50-150 m, is represented by the Pelamis an articulated attenuator with length 140-180m and 4m in diameter. A 1 MW Nearshore device operating in depths ranging from 20-80m, represented by a point absorber with a diameter of 20 meters; and lastly a Shallow 600kW device operating in shallow waters with a maximum depth of 20 m, represented by a terminator surge-oriented device. The power matrices of the devices that were integrated into the model are shown in Figure 3.2 to Figure 3.4.

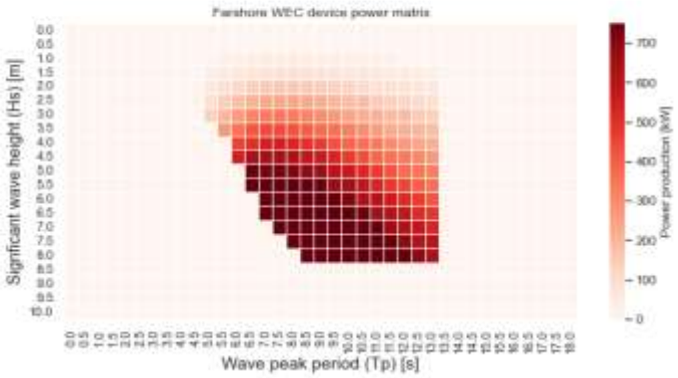

Figure 3.2 Farshore Wave Energy Converter 750kw Power Matrix. Range depth 50-150 m.

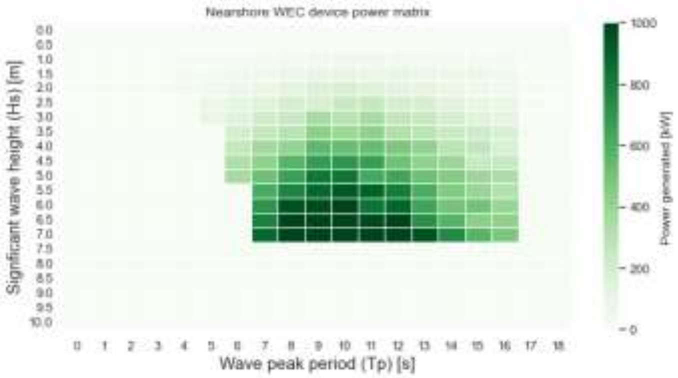

Figure 3.3 Nearshore Wave Energy Converter Power Matrix. Range depth 20-80 m.

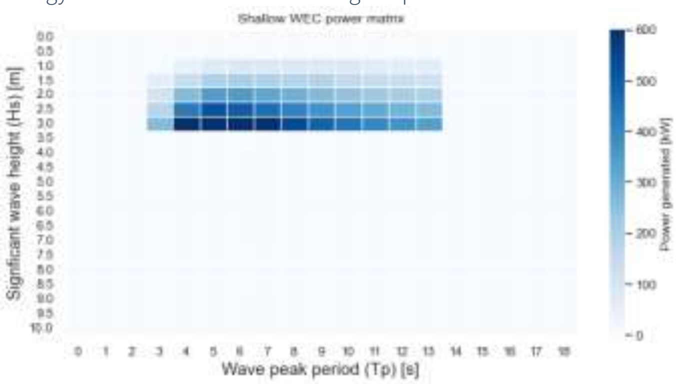

Figure 3.4 Shallow Wave Energy Converter Power Matrix. Range depth 0-20 m.

Different devices generate their maximum power output at different wave heights and peak wave periods, attributed to the device characteristics. The Farshore device, which operates at depths from 50 to 150 m, is optimized to generate its maximum output at wave heights between 5 and 8 m and wave peak periods ranging from 6 to 12.5 seconds. Meanwhile, the nearshore device produces its maximum output on wave heights between 6 and 7 meters and between wave periods of 8 and 13 seconds. The shallow device is optimized for milder conditions, where the power can be generated by the device in sea states characterized between 1 and 3 meters of wave height and wave periods ranging from 3 to 14 seconds.

The WEC function incorporated in PyPSA is subsequently coupled with the metocean conditions of every sea state at every grid cell and time step obtained from ECMWF's re-analysis ERA5 dataset (Hersbach et al., 2020), allowing us to estimate the capacity factor of each raster cell. In our consideration, the usable area i.e., how much is the maximum installed wave generation capacity is computed, here a packing density of 20MW/km^2 was considered feasible by Lavidas & Blok (2021).

The usable area for WECs is restricted by the operational water depths determined for each device. In addition, all nature reserves and restricted areas listed in the Natura 2000 database are excluded.

Because PyPSA-Eur partitions the different countries into Voronoi cells and the cutout of the weather data is finer than them, it estimates the distribution of generators across the grid cells within each Voronoi cell. To compute this generator layout, the installable potential is multiplied by the capacity factor at each grid cell. This follows the logic to install more generators at cells with a higher capacity factor. Once this layout is computed it is used to calculate the generation availability time series. In the end, Voronoi cells serve as nodal regions that are used as catchment areas for aggregated electricity loads, renewable resource potentials, and different generator and storage capacities, etc.

3.3 Learning Curves

3.3.1 Background

This thesis aims to explore the added value potential and implications of wave energy in a greenfield-based optimization of a 100% renewable energy scenario with 2030, 2040, and 2050 horizons. As seen in the problem formulation, the objective function seeks to minimize the total costs of the power system, thus the cost of generating technologies is a key factor towards the installation of these technologies under the solution found by the optimization.

Therefore, the penetration of wave energy under the renewable energy scenario is not only dependent on its cost but also the cost of competing renewables such as wind and solar, which have achieved relevant cost reductions over the last decade. For this reason, technological learning, the process under which cost reductions are achieved as a result of production growth, is considered in this thesis for wave energy devices. Technological learning is modeled through the one factor-learning curve approach.

A learning curve, also known as an experience curve, expresses that the costs decrease by a constant fraction with each doubling of the total number of units produced. It is however important to mention that these reductions are an empirical finding, as the factors that influence cost reductions remain unclear, thus, uncertainty is involved while estimating future technology costs. Some learning factors that can influence cost reductions are; learning by doing; learning by research; learning by interaction and knowledge diffusion; learning by upscaling manufacturing capabilities; and learning by upsizing of a product.

This approach is specifically employed to estimate the capital cost of wave energy in the 2030, 2040, and 2050 horizons and will serve as the basis for the set of modeled scenarios to explore the penetration of WECs, described in the following section. Furthermore, WEC cost reductions and the forecasted costs are modeled as an exogenous variable and serve as a parameter for the PyPSA-Eur model. The learning effect, when the cost of the first unit is unknown, can be written as:

$$C_{p2} = C_{p1} \cdot \left(\frac{P_2}{P_1}\right)^b \tag{3.12}$$

Where C_{p1} is the cost per unit after the cumulative production of P_1 units, C_{p2} is the cost per unit after the cumulative production of P_2, and b is the experience index, which defines the effectiveness with which the learning takes place. The formulation implies that after each doubling of production, the price is multiplied by a factor of 2^b, called the progress rate (PR). The learning rate is defined as $1\text{-}PR$ and refers to the reduction fraction after each doubling. So, a progress ratio of 90% equals a learning rate of 10% and thus means that unit production cost would decline by 10% and reach 90% of its original value whenever the production doubles (Blok & Nieuwlaar, 2020; Nihan Karali et al., 2015).

3.3.2 WEC Learning Curves

To project the potential cost reductions of WEC, and their respective capital costs of the technology in 2030, 2040, and 2050, a forecast of future capacity deployment of wave energy was estimated according to literature and European ocean energy targets. As outlined in the Offshore Renewable Energy Strategy, the ambition is to reach 40 GW of installed capacity of ocean energy (such as wave and tidal) by 2050, 1 GW by 2030, and 100 MW by 2025 (European Commission, 2020a). Nonetheless, the 1 GW target may even be conservative, as based on announced projects, the ocean energy pipeline expects 2.4 GW in Europe and 2.9 GW worldwide by 2030, in line with the optimistic scenario of the JRC's market study on ocean energy (European Commission, 2022d; Xavier Guillou, 2018). Moreover, the ocean energy industry has higher ambitions than the European Commission, aiming to install 100 GW of ocean energy by 2050 in Europe (European Commission, 2020b; OEE, 2020).

The forecast of future wave energy capacity deployment used in this research is shown in Figure 3.5. As a starting point, by the year 2020, 12 MW of wave energy have been deployed in Europe. In 2021, 681 KW were deployed, and 2.8 MW are slated for installation in 2022 (Ocean Energy Europe, 2022). Between 2023 and 2026 approximately 14.5 MW are installed with a year-on-year growth rate of 50% representing pilot projects with lower TRL levels, while from 2026 to 2030 approximately 284 MW are installed in order to reach 0.5 GW by 2030, as estimated by the JRC's and Ocean Energy Europe optimistic wave energy deployment scenarios.

These increased capacity additions represent the first commercial-stage testing of wave energy farms. During the decade leading to 2040, an annual growth rate of 25% is assumed, reaching a cumulative installed capacity of wave energy of 7.8 GW by the end of the decade. Deemed feasible as market assessments from the International Energy Agency estimate that 12 GW of Ocean energy could be installed by 2040 (European Commission, 2020b; IEA, 2019b). Between 2040 and 2050, the annual growth rate slows down to 12% to reach just above 40 GW of cumulative capacity by 2050. This implies that the European target of 40 GW of ocean energy by 2050 could be met by wave energy only. However, this can be justified by the higher ambition of the industry of 100 GW by 2050, deployments made in the rest of the world, and that wave energy is the only ocean technology currently considered in the model.

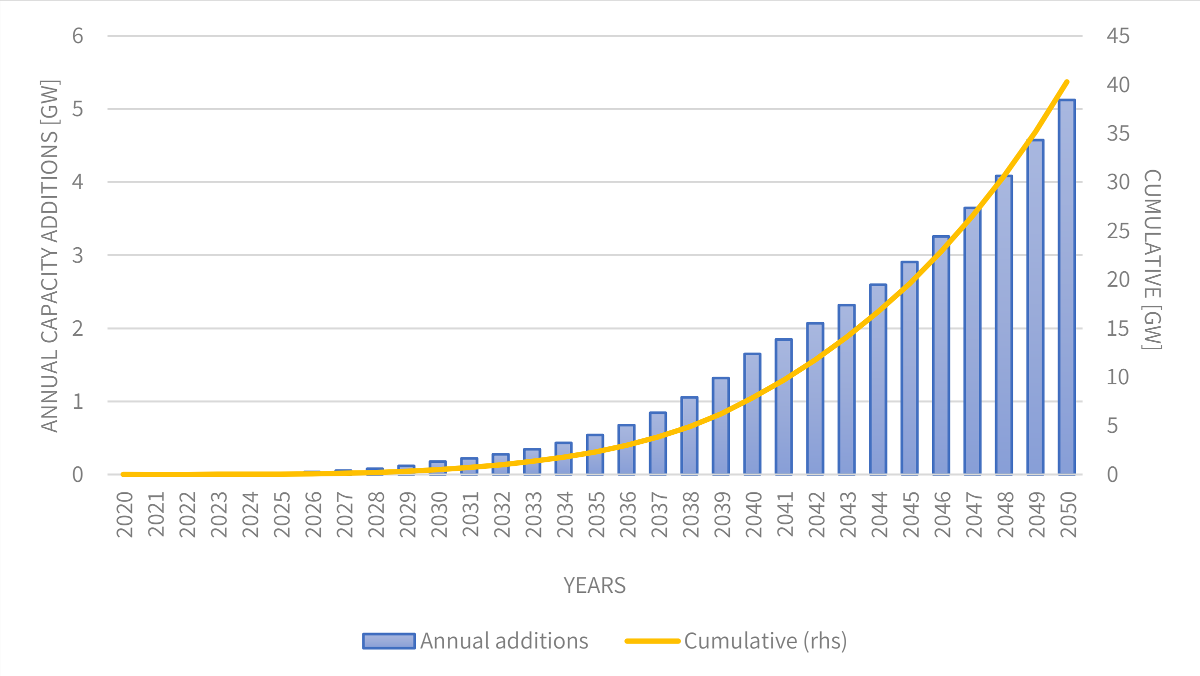

Figure 3.5 Projected capacity additions of wave energy 2020-2050

As mentioned in section 3.3, the research employed a one-factor learning curve approach to estimate the capital cost of WEC in 2030, 2040, and 2050. A learning curve visualizes the costs decrease by a constant fraction with each doubling of the total number of units. Research on energy cost dynamics has concluded that learning is responsible for cost reductions, and the simplicity of the one-factor learning curve approach has been practical and has enabled renewable energy system models to assess required cost reduction. Nonetheless, in reality, using a single parameter to represent experience and other learning processes does not properly describe the complex dynamics leading to cost reductions, which involve activities from learning by researching and doing, to economies of scale and other market phenomenon (Elia et al., 2021). Something that has been observed, is that the learning curve is not necessarily linear, but rather S-Shaped, being rather flat during early stages, accelerating during commercialization and growth, and flattening as the technology reaches maturity (Grafström et al., 2021; Samadi, 2018). Because of this, to estimate the potential cost reductions of wave energy within the model and across the different horizons, a variable learning rate of 12% was used between 2020 and 2030, 8% between 2030 to 2040, and 4% between 2040 and 2050, assuming a conservative S-shaped cost trajectory for the technology.

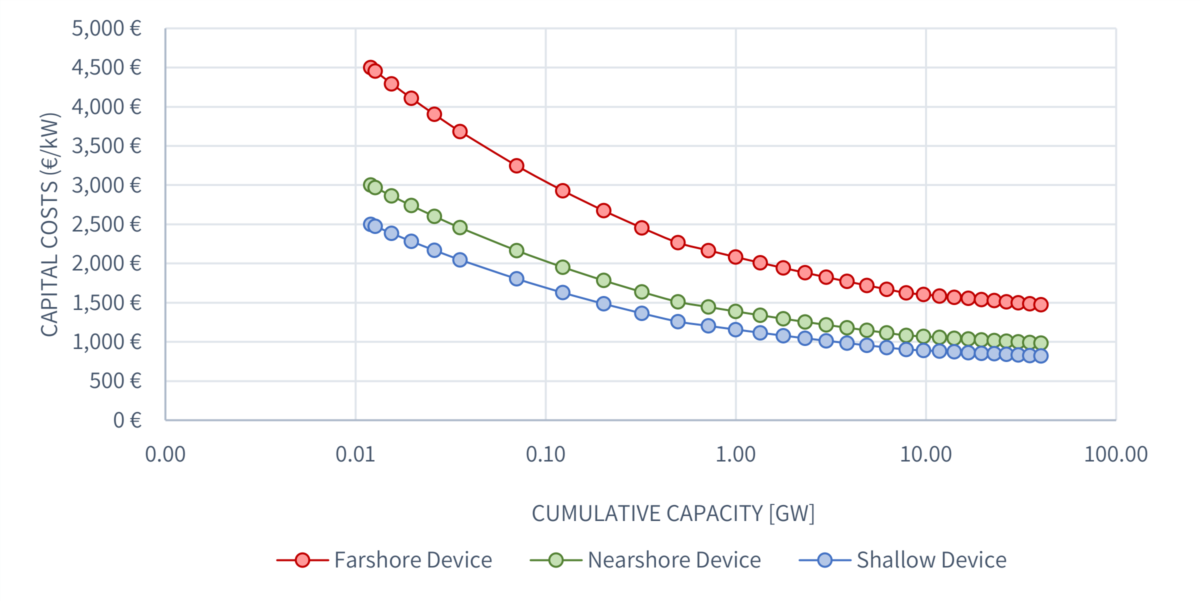

Figure 3.6 Learning curves for different WEC devices

Figure 3.6 showcases the learning curve of each type of WEC included according to capacity on a logarithmic scale. All devices share the same cost reduction trend over increased installed capacity and are differentiated only by the initial capital cost. Combining these learning curves of WEC devices with the projected capacities shown in Figure 3.5 produces the capital cost per unit at a given point in time. The results are shown in Figure 3.7. It is important to mention that it is assumed that the cumulative capacity over time leading to 40 GW in 2050 has an equal impact on the learning curve of each device. In other words, it is assumed that the deployment of any type of wave energy converter allows for the cost reduction benefit by earning for any other type of WEC in the future, without considering the specific technology method.

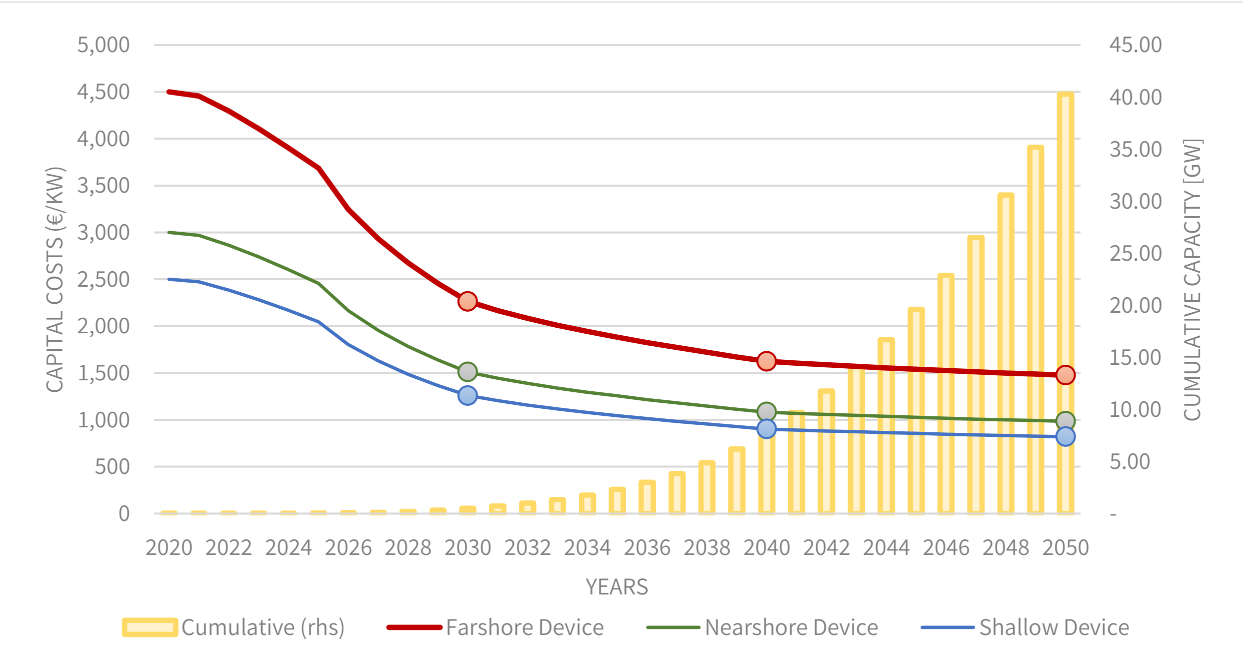

Figure 3.7 Projected Cost reduction of WEC, Experience curve of technologies (lines, right), cumulative installed capacity (bar, left)

It can be observed in Figure 3.7 that the cost reductions of all devices follow the same trajectory, being the initial capital cost the differentiating factor. The Farshore device has an initial cost of 4,500 €/kW reaching a capital cost of 2,264 €/kW by 2030 with a learning rate of 12% during this decade, a capital cost of 1,624 €/kW by 2040 with a learning rate of 8%, and 1,475 €/kW by 2050. In a similar manner, the initial cost of the Nearshore and Shallow devices were set at 3,000 €/kW and 2,500 €/kW, respectively. Applying the same variable learning rates, the expected capital costs of the Nearshore device are 1,509 €/kW by 2030, 1,082 €/kW by 2040, and 983 €/kW by 2050. For the Shallow device, the initial capital cost is 2,500 €/kW and results in a capital cost of 1,258 €/kW by 2030, 902 €/kW by 2040, and 819 €/kW by 2050.

3.4 Model Setup & Scenarios

Scope

The scope of the research is to explore the hidden value opportunities and implications of wave energy under a 100% multi-renewable power system, under a greenfield approach, and a 2030, 2040, and 2050 horizon. This, to answer the stated research questions related to; (i) The general dynamics of a European multi-renewable power system that considers wave energy; (ii) the evolution of power system components under a multi-renewable power system considering wave energy; and (iii) Identifying the potential role of wave energy future multi-renewable European power systems.

To answer these questions, a set of scenarios is modelled mainly differentiated by capital cost forecasts of wave energy estimated from different learning curves and expected capacity additions over this decade. These differentiated capital costs will ultimately lead to different wave energy penetration levels in the European power system, and their implications and interactions are assessed.

The geographical scope of the modelled scenarios is Europe, including the UK, but more specifically the network topology of the European transmission network ENTSO-E, updated in PyPSA-Eur until 2019. Under the optimization, new transmission infrastructure cannot be placed, but existing one can be expanded, limiting the total volume of line expansion to 25% of existing line capacities.

The research and optimization scenarios cover a period of one year, and weather and electricity demand data employed are from the year 2018 and are extracted by PyPSA-Eur from the ERA 5 dataset and the ENTSO-E transparency platform. The resolution of weather data is 0.25° x 0.25° per grid cell. The optimizations are executed under an hourly resolution, commonly used on various high-share renewable energy studies (Hansen et al., 2019), as it allows for a sufficient level of detail to consider the variability and the required system flexibility of power systems with variable renewable generation.

3.4.1 Technologies

The technologies considered in greenfield multi-renewable power system optimization at different time horizons are presented below. An overview of them and their respective technology costs are shown in Table 3.4 at the end of this section.

3.4.1.1 Wave Energy

First and foremost, the novel addition and key contribution of this research. Three different wave energy converters are modeled; a Farshore 750kW device that operates on depths below sea level ranging from 50-150 m, representing the Pelamis an articulated attenuator; A 1 MW Nearshore device operating in depths ranging from 20-80m, represented by a point absorber with a diameter of 20 meters; and lastly a Shallow 600kW device operating in shallow waters with a maximum depth of 20 m, represented by a terminator surge-oriented device. The power matrices employed to estimate the potential power output are presented in Figure 3.2 to Figure 3.4. The devices are constrained by the eligible land defined by Corine Land use codes and exclude natural protected areas included in the Natura 2000. All devices are set with a packing rate of 20 MW/km^2, deemed feasible by Lavidas & Blok (2021). For offshore technologies, such as wave energy, the average distance from the node is calculated as an underwater fraction to estimate the infrastructure costs of underwater lines and connection costs, which is ultimately added to the capital cost of the technology.

3.4.1.2 Offshore Wind

Two different offshore wind technologies are considered in the model; Bottom-Fixed Offshore Wind and Floating Offshore wind. Within the Bottom-Fixed offshore wind, two subcategories are considered in the model differentiated by either AC or DC connection, defined by their distance from shore. DC bottom-fixed turbines can be installed up a maximum distance from the shore of 30 km and a maximum water depth of 50 m. While the AC bottom-fixed wind turbine can be installed from a distance to shore greater than 30 km but the maximum water depth remains at 50 m. In brief, the wind speeds at 100m above ground are extrapolated to the turbine hub height and the capacity factor of each raster cell and time step is determined with the turbine's power curve.

Both AC and DC bottom-fixed offshore wind are represented in the model with the NREL's 8 MW reference wind turbine from NREL Turbine Archive (National Renewable Energy Laboratory (NREL), 2022). The key parameters of the turbine and its power curve are presented in Table 3.1 and Figure 3.8, respectively.

Table 3.1 Key Parameters of NREL 8MW reference wind turbine for bottom-fixed option
Source: (National Renewable Energy Laboratory (NREL), 2022)

Item	Value	Units
Name	NREL Reference 8MW	N/A
Rated Power	8000	kW
Rated Wind Speed	12	m/s
Cut-in Wind Speed	4	m/s
Cut-out Wind Speed	25	m/s
Rotor Diameter	180	m
Hub Height	112	m
Control	Pitch Regulated	N/A

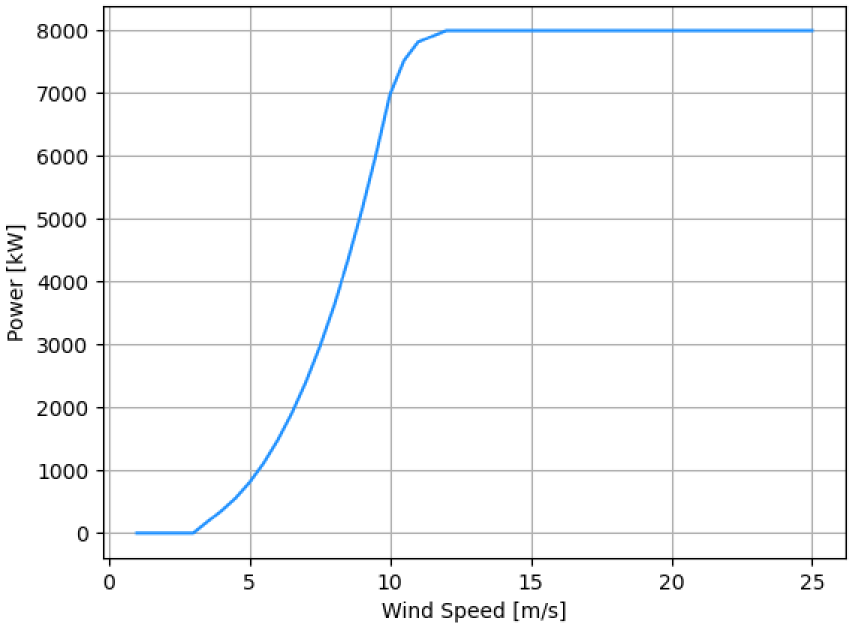

Figure 3.8 Power curve of NREL 8MW reference wind turbine
Source: (National Renewable Energy Laboratory (NREL), 2022)

Given the dimensions and characteristics of the 8MW wind turbine, an approximate technical packing rate of 16 MW/km^2 (2 turbines/km^2) assuming a 6Dx4D (distance side by side and front to back, respectively) array was estimated. However, to consider other social and political factors such as social acceptance, a packing rate of 8 MW/km^2 is assumed in the model.

Floating Offshore Wind is another novel addition to the model, as the original PyPSA-Eur only considers bottom-fixed wind turbines. In essence, both bottom-fixed and floating are modeled in the same manner but are differentiated by the type of turbine and the parameters of capital cost, maximum distance from shore, and maximum water depth. Floating offshore is eligible for sites characterized by a maximum distance from the shore of 50 km, and a water depth ranging from 50 to 250 m. It is assumed that the turbines are connected by AC lines, and it is represented by NREL's 15 MW reference offshore wind turbine. The characteristics and power curve of the wind turbine area are presented in Table 3.2 and Figure 3.9.

Table 3.2 Key Parameters of NREL 15MW reference floating wind turbine
Source: (National Renewable Energy Laboratory (NREL), 2022)

Item	Value	Units
Name	OR Cost Reference 15 MW	N/A
Rated Power	15000	kW
Rated Wind Speed	11	m/s
Cut-in Wind Speed	4	m/s
Cut-out Wind Speed	25	m/s
Rotor Diameter	248	m
Hub Height	149	m
Drivetrain	Direct Drive	N/A

Control	Pitch Regulated	N/A
IEC Class		N/A

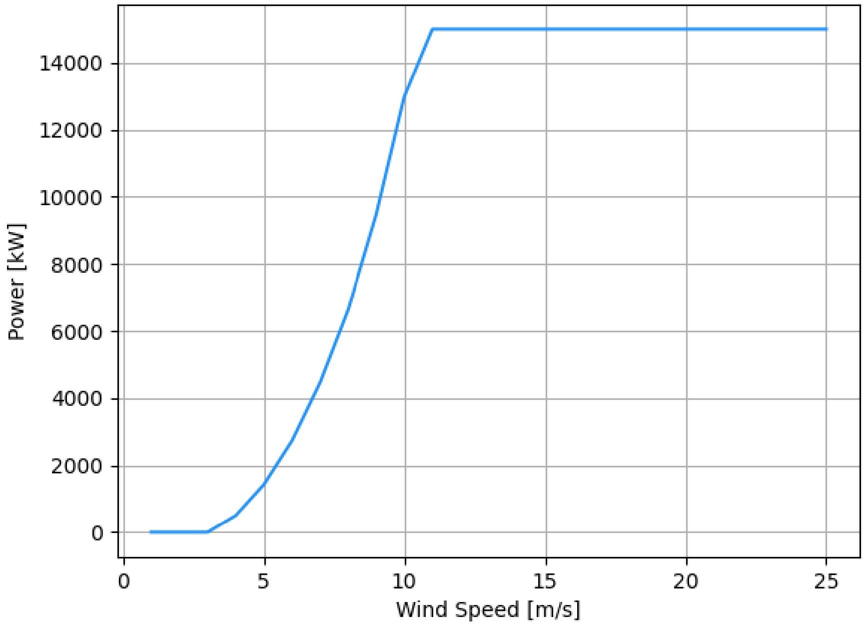

Figure 3.9 Power curve of NREL 15MW reference wind turbine
Source: (National Renewable Energy Laboratory (NREL), 2022)

Similarly, to bottom-fixed offshore, the technical packing rate was estimated at 15 MW/km^2 but was set at 7 MW/km^2 to consider other factors at play. In addition, in the same manner as wave energy, the average underwater fraction of offshore wind technologies are calculated, and their respective capital costs are included in the technology.

3.4.1.3 Onshore wind

Onshore wind technology is part of the original PyPSA-Eur model. The default turbine and restrictions of the PyPSA-Eur model were left untouched. In the same manner, as offshore wind, the wind speeds at 100m above ground are extrapolated to the turbine hub height and the capacity factor of each raster cell and time step is determined with the turbine's power curve.

This onshore wind technology is represented by the 3 MW Vestas V112 wind turbine with a hub height of 80m, whose characteristics and power curve are shown below. The technical potential density is 10 MW / km^2 but is set at 3 MW / km^2 to consider public acceptance and competing land use activities. The eligible type of land excludes nature conservation areas in the Natura 2000 database and onshore wind can only be built in land use types of the CORINE Land Cover database related to *Agricultural areas*, *Forest and semi natural areas*. In addition, land within 1km of U*rban fabric* and *Industrial, Commercial and Transport* land codes is also restricted for the deployment of onshore wind, as well *wetlands*, *beaches*, *dunes*, and *sands*. (Hörsch et al., 2018a)

Table 3.3 Key Parameters of Vestas 112 3MW onshore wind turbine
Source: (The wind power, 2022)

Item	Value	Units
Name	Vestas 112 3 MW	N/A

Rated Power	3000	kW
Rated Wind Speed	12	m/s
Cut-in Wind Speed	3	m/s
Cut-out Wind Speed	25	m/s
Rotor Diameter	112	m
Hub Height	N/A	m

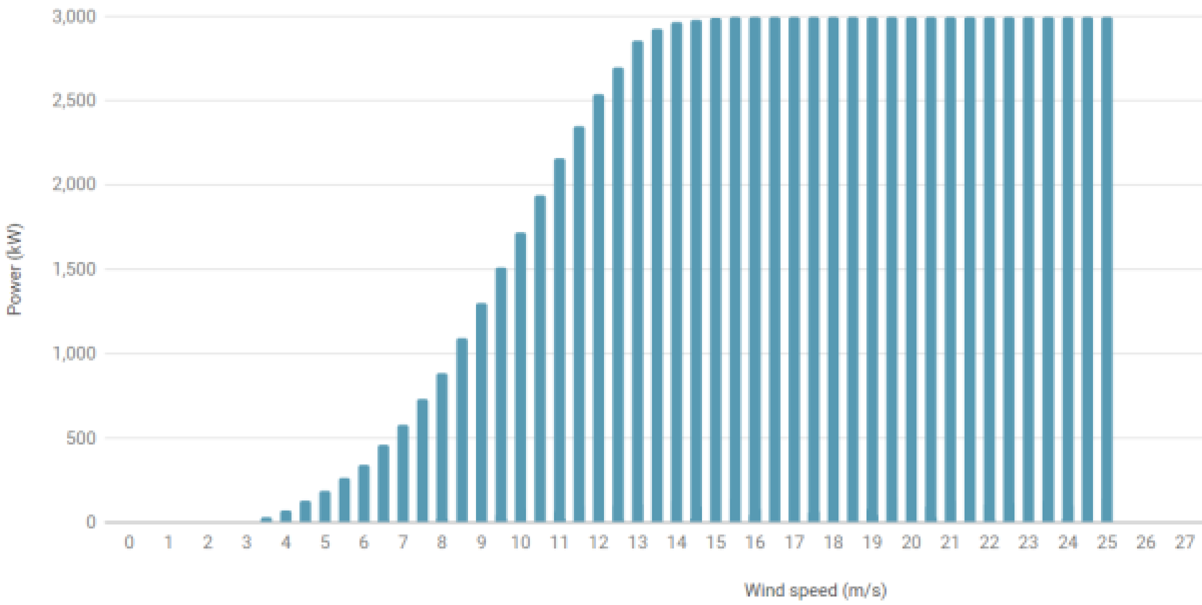

Figure 3.10 power curve of Vestas 112 3MW wind turbine
Source: (The wind power, 2022)

3.4.1.4 Solar Photovoltaic

Solar photovoltaic generation is also part of the original PyPSA-Eur model and was considered in this analysis. The solar conversion function, availability time series, and installable capacity potential are based on the direct and diffuse solar irradiance from the ERA 5 dataset. The photovoltaic generation of a panel with a nominal capacity at a point in time and respective grid cell is calculated from the surface solar irradiance. The solar azimuth and altitude are used to estimate the total panel irradiation using geometric relationships of the trajectory of the sun and the tilt of the panel surface. Solar panels are set facing south at an angle of 35 degrees. The active power output from the total irradiation and ambient temperature is determined by the electric model by Huld et al. (2010). (Hörsch et al., 2018a)

Similarly, to onshore wind, permitted CORINE land use types for solar deployment are *Artificial surfaces*, most *Agricultural areas* except for those with forests, and then including only a few sub-categories of *Forest and semi natural areas: Scrub and/or herbaceous vegetation associations, bare rocks and sparsely vegetated areas.*

The technical maximal installable potential is 145 MW/ km^2, which corresponds to a full surface of solar cells, but it is set at 1% of the technical potential (1.45 MW/ km^2) to account for other technical, economic, and social factors. Furthermore, within the model, 50% of the installed capacities are assumed to be solar rooftop-mounted systems and 50% are utility-scale solar parks. (Hörsch et al., 2018a)

3.4.1.5 Geothermal

Geothermal plants are the only conventional power generators considered in the 100% renewable energy scenarios. Developers of PyPSA-Eur gathered and collected a power plant dataset from multiple available databases, for which existing geothermal power plants are aggregated. Within the model, these types of generators are not expandable, implying that their capacity cannot be expanded or reduced. It is important to mention that some existing geothermal capacities are not available in the model due to a lack of data in many countries.

3.4.1.6 Hydroelectric generation

Similar to conventional power plants such as geothermal, within the PyPSA-Eur workflow, existing hydroelectric capacities are gathered and collected. They were categorized into run-of-river, reservoir, and pumped storage (PHS). Reservoir and pumped storage are treated as power storage units, and their storage capacities are estimated by distributing the country-aggregated energy storage capacities in proportion to power capacity. Run-of-river and reservoir hydro capacities receive an hourly-resolved inflow of energy estimated with run-off data from the ERA 5.

Similar to conventional power plants, hydroelectric generation technologies are assumed to remain at the currently installed capacities and cannot be expanded during the optimization. Furthermore, hydroelectric generation capacities in every country are fixed, and they are considered to be fully amortized. (Hörsch et al., 2018a).

3.4.1.7 Storage Units

Within the PyPSA framework, storage units attach to a single bus and are used for inter-temporal power shifting. Two types of storage are modeled within PyPSA-Eur in addition to PHS; Battery storage representing short-term storage options; and Hydrogen storage as a long-term storage option.

The storage capacities are assumed to be proportional to the power capacities, with the ratio "Maximum hours" representing the time in which a storage unit can be fully charged or discharged at maximum power. The maximum hours for battery storage is 6 hours, while hydrogen storage is set at 168 hours.

Hydrogen storage is modeled as an overground steel tank, hydrogen electrolyzers, and a hydrogen fuel cell. The round-trip efficiency of hydrogen storage is 46.4%, with the efficiency of the electrolyzers set at 80% and the fuel cell at 58%. Meanwhile, battery storage is modeled as a battery and a battery inverter with an efficiency of 90%, giving the battery a round-trip efficiency of 81%. Standing losses in the storage are neglected (Hörsch et al., 2018a; Schlachtberger et al., 2018).

3.4.2 Scenarios

In order to answer the research questions three different scenarios are proposed. Given that the objective function of the model seeks to minimize costs across the modeled power system, the capital cost of WEC and the cost of competing renewables and storage technologies are key drivers toward the allocation of wave energy within the model optimization.

Considering these, three different scenarios are envisioned towards the 2030, 2040, and 2050 horizons seeking to consider expected cost reductions of WEC and other generating technologies as well as planned expansions of the transmission network through the following decades. The network expansion constraints for 2030 and 2040 are based on the identified cross-border capacity increase needs of ENTSO-E Ten-Year Network Development Plan 2022 (ENTSO-E, 2022c), while for 2050 an additional 25% from 2040 estimate was assumed feasible. Furthermore, to assess the impact that network expansion can have over the multi-renewable power system, a sensitivity analysis is performed on the 2050 network scenario. Figure 3.11 showcases an overview of the modeled scenarios.

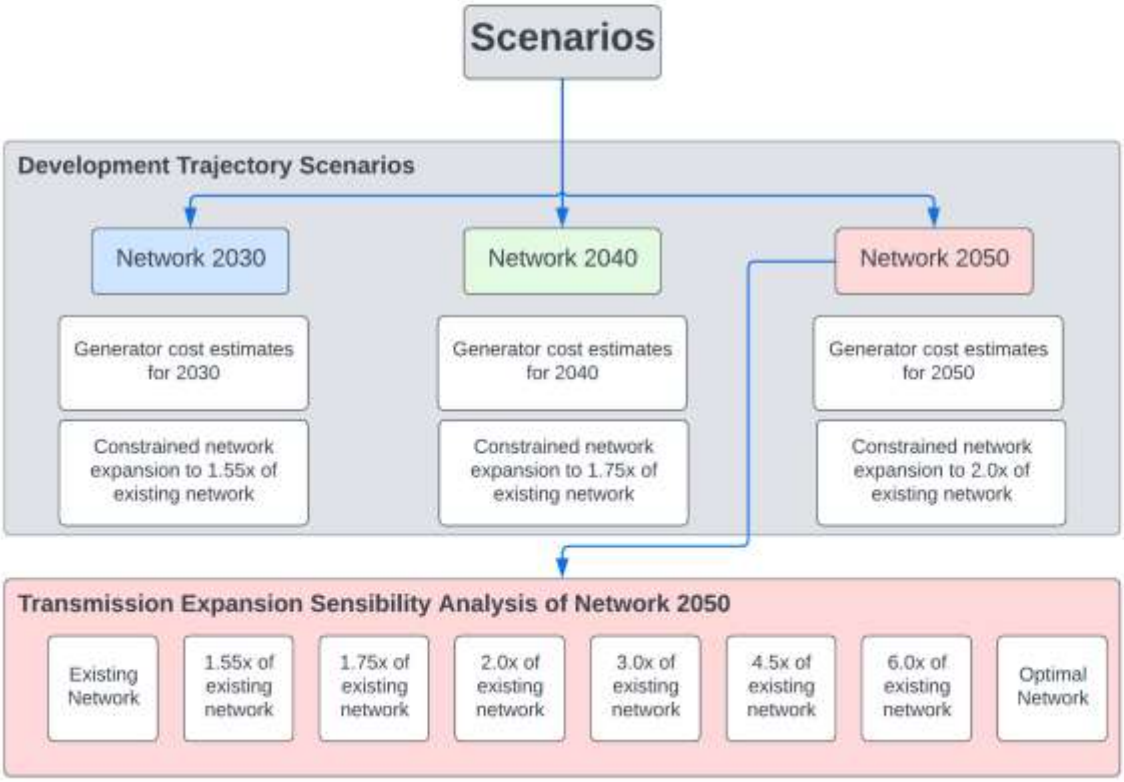

Figure 3.11 Modeled Scenarios Overview

This temporal differentiation allows for the consideration of potential cost reductions of WECs and other technologies over the following decades. WEC cost reductions were estimated through the learning curve approach in section 3.3. For most renewable and storage technologies, a mix of cost estimates and other assumptions for 2030, 2040, and 2050 were gathered from the EU Reference Scenario technology assumptions file prepared by the JRC (European Commission, 2021) and from the Technology Data Catalogue for Electricity and heating production Danish Energy Agency (Danish Energy Agency, 2022). Cost assumptions for batteries and hydrogen storage tanks were maintained from the original assumptions of the PyPSA-Eur model and dataset. The cost, lifetime, and efficiency assumptions for the key technologies of the different scenarios are summarized in Table 3.4.

Table 3.4 Costs, lifetime and efficiency values assumed for the model and scenarios

Technology	Overnight Capital cost [€]	Unit	FOM[a] [%/year]	Lifetime [years]	Efficiency	Source
Network 2030						
Wave Farshore	2516	€/kW	12	25		
Wave Nearshore	2012	€/kW	8	25		
Wave Shallow	1509	€/kW	5	25		
Onshore wind	1001	€/kW	3.3	30		JRC[c]
Offshore wind bottom-fixed	1754	€/kW	5	25		JRC[c]
Offshore wind floating	2408	€/kW	13	25		JRC[c]
Solar PV utility scale	384	€/kW	3	25		JRC[c]
Solar PV rooftop	539	€/kW	2	25		JRC[c]
Batteries	192	USD/kWh		15	0.81	PyPSA-Eur[d]
Battery inverter	411	USD/kW	5	20	0.9	PyPSA-Eur[d]
Hydrogen storage[b]	11.2	USD/kW	0	20	0.46	PyPSA-Eur[d]
Hydrogen electrolysis	920	€/kW	4	18	0.8	JRC[c]
Hydrogen fuel cell	1300	€/kW	5	10	0.58	DEA[e]
Network 2040						
Wave farshore	1804	€/kW	12	25		
Wave nearshore	1443	€/kW	8	25		
Wave Shallow	1083	€/kW	5	25		
Onshore wind	961	€/kW	3.3	30		JRC[c]
Offshore wind bottom-fixed	1688	€/kW	5	25		JRC[c]
Offshore wind floating	2339	€/kW	10	25		JRC[c]
Solar PV utility scale	368	€/kW	3	25		JRC[c]
Solar PV rooftop	517	€/kW	2	25		JRC[c]
Batteries	192	USD/kWh		15	0.81	PyPSA-Eur[d]
Battery inverter	411	USD/kW	5	20	0.9	PyPSA-Eur[d]
Hydrogen storage[b]	11.2	USD/kW	0	20	0.46	PyPSA-Eur[d]
Hydrogen electrolysis	920	€/kW	4	18	0.8	JRC[c]
Hydrogen fuel cell	1300	€/kW	5	10	0.58	DEA[e]
Network 2050						
Wave farshore	1639	€/kW	9	25		
Wave nearshore	1311	€/kW	5	25		
Wave Shallow	983.61	€/kW	3	25		
Onshore wind	933	€/kW	3.3	30		JRC[c]
Offshore wind bottom-fixed	1622	€/kW	5	25		JRC[c]
Offshore wind floating	2268	€/kW	10	25		JRC[c]
Solar PV utility scale	352	€/kW	3	25		JRC[c]
Solar PV rooftop	496	€/kW	2	25		JRC[c]
Batteries	192	USD/kWh		15	0.81	PyPSA-Eur[d]
Battery inverter	411	USD/kW	5	20	0.9	PyPSA-Eur[d]
Hydrogen storage[b]	11.2	USD/kW	0	20	0.46	PyPSA-Eur[d]
Hydrogen electrolysis	920	€/kW	4	18	0.8	JRC[c]
Hydrogen fuel cell	1300	€/kW	5	10	0.58	DEA[e]

[a] Fixed operation and maintenance (FOM) costs as a percentage of the overnight cost per year.
[b] Hydrogen Overground steel tanks are assumed (Budischak et al., 2013)
[c] (European Commission, 2021)
[d] Existing Assumption in PyPSA-Eur from (Budischak et al., 2013)
[e] (Danish Energy Agency, 2022)

For each scenario, a future, 100% renewable European Electricity network is modeled via a greenfield optimization. In other words, the European power system is built from scratch, except for existing hydroelectric and geothermal capacities. For other renewables and storage technologies, the installed capacities and their respective dispatch at every time step are optimized depending on the geographical and weather-dependent potentials.

This approach is appropriate for the defined research questions and objectives of the thesis, i.e. to understand the general system dynamics of wave energy integration and its potential impact on future high and multi-renewable energy scenarios. Particularly its interaction with storage technologies, competing mature renewables, and network expansion. The addition of wave energy, and floating wind to PyPSA-Eur and the results of this work can enable and inspire more detailed investigations.

3.4.3 Other assumptions and Parameters

3.4.3.1 Weather Data

As mentioned before, to derive the availability times series of and estimate the capacity factor of renewables at their respective location, PyPSA-Eur employs the ERA5 weather dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF) (Hersbach et al., 2020). To achieve this, the PyPSA-Eur workflow retrieves solar irradiation, surface roughness, wind speeds at 100m, surface run-off from rainfall, significant height of combined wind waves and swell, and peak wave period. The dataset provides hourly values of each of the parameters since 1950 (M. S. F. Neumann et al., 2021). Although different reference weather years can be chosen for the optimization, the scenarios and analysis throughout this thesis are based on the year 2018. Furthermore, The resolution of weather data is 0.25° x 0.25° per grid cell, which is equivalent to about 27 km x 27km.

3.4.3.1 Electricity demand

As mentioned in section 2.4.4.3, the PyPSA-Eur model gathers data on electricity consumption from historical data from ENTSO-E statistics. Similarly, to weather data, the year 2018 was chosen as the reference year. However, given that the scenarios modeled are at different time horizons, the load time series was multiplied by a global scaling factor.

The aim was to have electricity demand evolve as the years progressed. The scaling factor was estimated using linear regression on historical electricity consumption data of Europe and forecasting it to 2050. Thus, the global scaling factors applied to the scenarios 2030, 2040, and 2050 are 1.10, 1.19, and 1.28, respectively. This simple assumption seeks to represent changes in electricity demand considering historical trends from 1990-2019. This implies that it does not consider the expected electrification of certain sectors due to decarbonization policies, as well as potential efficiency gains in the future.

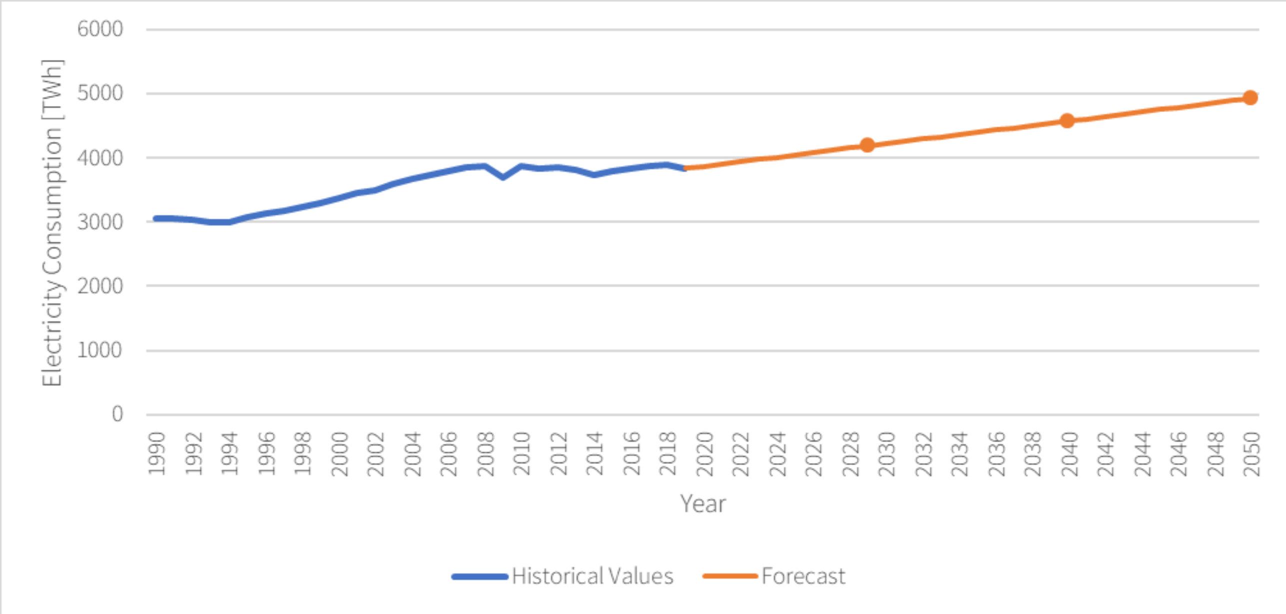

Figure 3.12 Forecast and Historical values of electricity consumption in Europe
Source: Electricity Consumption 1990-2019 (IEA, 2022)

3.4.3.2 Transmission Expansion Constraints

PyPSA-Eur, as one of the configuration features, allows specifying limits in line expansion during the optimization. This limit can either be a constraint on the total volume of line expansion of installed capacities or a constraint on the costs of the current transmission infrastructure. The volume constraint limits the total volume of line expansion by a certain factor (CAP_{trans}) defined in relation to the existing line capacities (CAP_{trans}^{today}). Thus, the sum of all transmission line capacities F_ℓ (HVAC and HVDC) multiplied by their lengths l_ℓ is restricted by CAP_{trans}, which can be modified for different simulations. (Hörsch & Brown, 2017)

$$\text{s.t} \qquad \sum_\ell l_\ell \cdot F_\ell \leq CAP_{trans} \qquad \forall \ell, t \qquad (4.1)$$

$$\text{where} \qquad CAP_{trans} = X_{const} \cdot CAP_{trans}^{today} \qquad \forall \ell, t \qquad (4.2)$$

Where X_{const} represents the capacity expansion constraint inputted into the model.

For the modeled scenarios, constraint in line volume was selected according to the time horizon, as well as performing a sensitivity analysis at different volumes to assess how this constraint impacts the cost-optimal configuration result. In essence, this constraint does not apply to each individual transmission line, but rather the total expansion of the network is limited. In that sense, the most welfare-increasing expansions are prioritized

The network expansion constraints for 2030 and 2040 are based on the identified cross-border capacity increase needs of ENTSO-E Ten-Year Network Development Plan 2022 (TYNDP), while for 2050 an additional 25% from 2040 estimate was assumed feasible. The TYNDP 2022 study identifies opportunities to make Europe's power system more efficient all over Europe. Specifically, it identified that 64 GW of additional cross-border capacity can be installed on over 50 borders, representing a 55%

increase in cross-border capacity. For the decade of 2040, the study identified space for 88 GW of additional cross-border capacity representing a 75% cross-border capacity increase from the current network (ENTSO-E, 2022c).

The 55% increase for 2030 and the 75% increase for 2040 were taken as exogenous parameters into the scenarios for their respective horizons. No information was found for the 2050 network, but an additional 25% increase in cross-border capacity over 2040 was considered feasible.

4. Results

In this section, the results of the research are presented. Firstly, the integration of wave energy converters and the estimated technical resource across Europe's coastlines are estimated by the model. Secondly, the results of the cost-optimal configurations of the development trajectory scenarios are presented in terms of their components, i.e., generation, storage, and transmission. In addition, the total system costs of the cost-optimal networks are presented, as well as a visual overview of the results.

4.1 Wave Energy in PyPSA-Eur

The novel integration of wave energy converters conversion functions paired with metocean data from ERA 5 into the PyPSA framework allowed for the first power analysis software to assess the wave energy resource across Europe's coastlines. By employing metocean data from the ERA5, specifically *Significant height of combined wind waves and swell* (H_s) and *Peak wave period* (T_p), the model is now capable of characterizing the sea state of every grid cell and every timestep across the year. Furthermore, by pairing these characterized sea states with the defined WEC power matrices shown in Figure 3.2 to Figure 3.4, the model can estimate the renewable wave energy capacity potentials restricted by depth, packing rate, and land; Derive the renewable wave generation availability time series of the WEC devices according to their power matrixes and the characterized sea-states; derive the capacity factor and power generation potential; and ultimately consider the wave energy resource and WECs in a cost-optimal power flow optimization of the European power system at the transmission network level covering the ENTSO-E area.

Figure 4.1 and Figure 4.2 visualize the wave resource assessment within Europe. They showcase the geographic potential of the maximum installable capacities of each WEC device and averaged capacity factor for the year 2018. Furthermore, by combining the maximum geographic capacity from the assumed land and depth restrictions and the yearly averaged capacity factor, the technical maximum energy that could be produced from each device is estimated for different regions across Europe's coastlines.

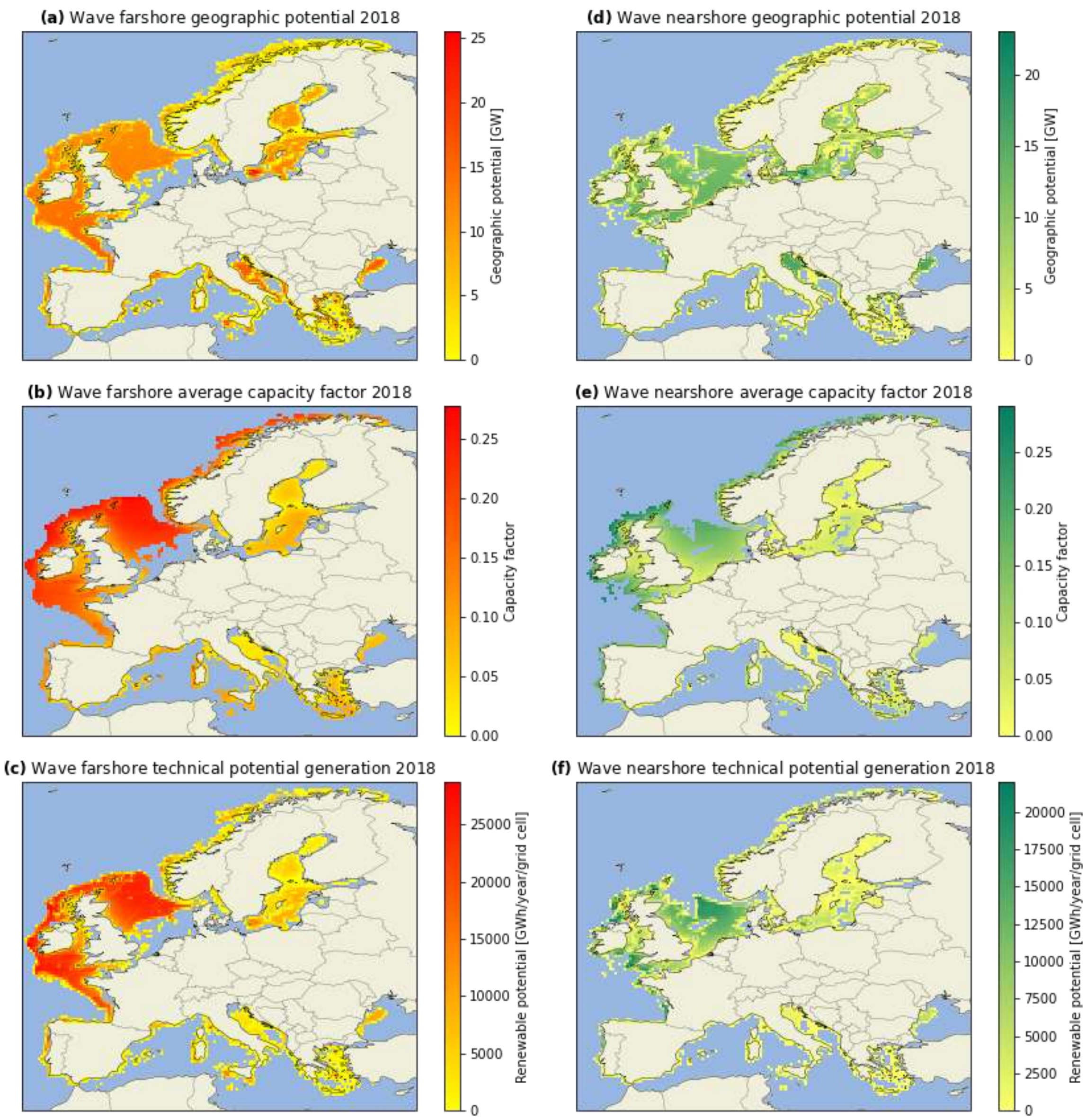

Figure 4.1 Geographic capacity potential, yearly averaged capacity factor, and renewable generation potential for the WEC Farshore (a, b, c) and WEC Nearshore (c, d, f) device, 2018 Europe

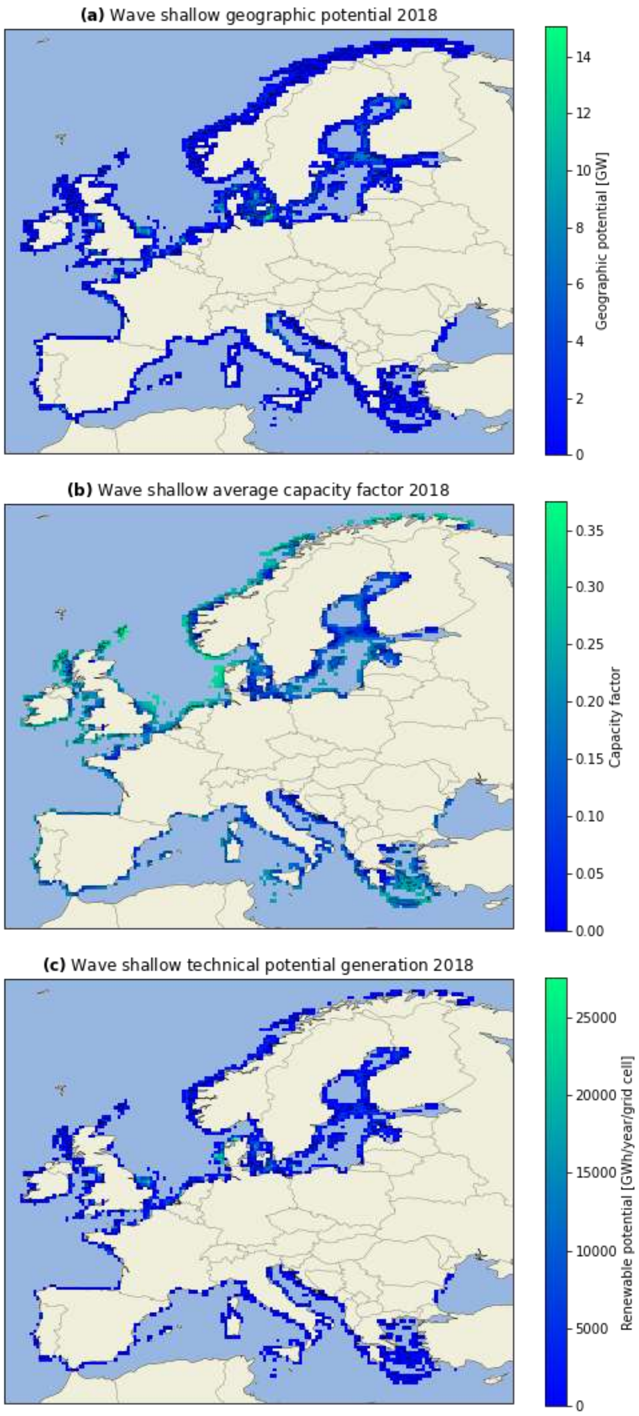

Figure 4.2 Geographic capacity potential (a), yearly averaged capacity factor (b), and renewable generation potential (c) for the WEC Shallow device, 2018 Europe

The geographic potential refers to the maximum installable capacity given input parameters of maximum and minimum depth, land restrictions, and packing rate for each device. In reality, the realized installed potential or practical resource depends on a variety of factors such as array types, WEC design, packing density, and marine spatial planning (i.e., colocation options). Furthermore, these technical aspects ultimately depend on political, social, economic, and environmental factors implying a balance not only between land availability, but also conservation efforts, landscape impact, social acceptance, and political will. However, given our configured constraints for each device, Table 4.1 presents the total geographic potentials for each device across the 24 countries with eligible areas to exploit wave energy, as well as the European Total.

Table 4.1 Geographic capacity potentials for each device across Europe [GW]

Countries	Farshore device	Nearshore device	Shallow device	Total
Total Europe	20307	14690	2483	37480
United Kingdom	6908	3856	318	11082
Norway	2255	1157	165	3577
Ireland	2126	603	50	2779
France	1796	654	90	2541
Sweden	1688	1673	400	3761
Italy	1180	752	246	2178
Greece	744	398	96	1238
Finland	685	762	396	1843
Croatia	429	347	25	801
Spain	424	188	37	648
Denmark	390	1203	378	1971
Poland	328	345	12	685
Romania	300	314	3	616
Estonia	296	312	69	677
Portugal	236	104	16	356
Latvia	222	285	30	538
Bulgaria	113	92	10	215
Albania	63	30	13	107
Lithuania	56	92	2	150
Montenegro	53	18	3	73
Germany	12	521	56	588
Netherlands	3	874	52	929
Belgium	N/A	110	16	126
Slovenia	N/A	3	1	4

Moreover, Figure 4.3 visually summarizes the information presented in Table 4.1. Great Britain has the highest potential in both the Farshore and Nearshore devices, with an installable capacity of 6.9 TW and 3.8 TW, respectively. However, for the Shallow device, Sweden, Finland, and Denmark have the highest installable potential with capacities close to 400 TW. Regarding the optimization, these geographical potentials represent the maximum extendable capacity of the respective wave energy converters that the PyPSA-Eur considers for each country node. Note that these geographic potentials are noncumulative, as particularly the Farshore and Nearshore device share depth eligibility criteria.

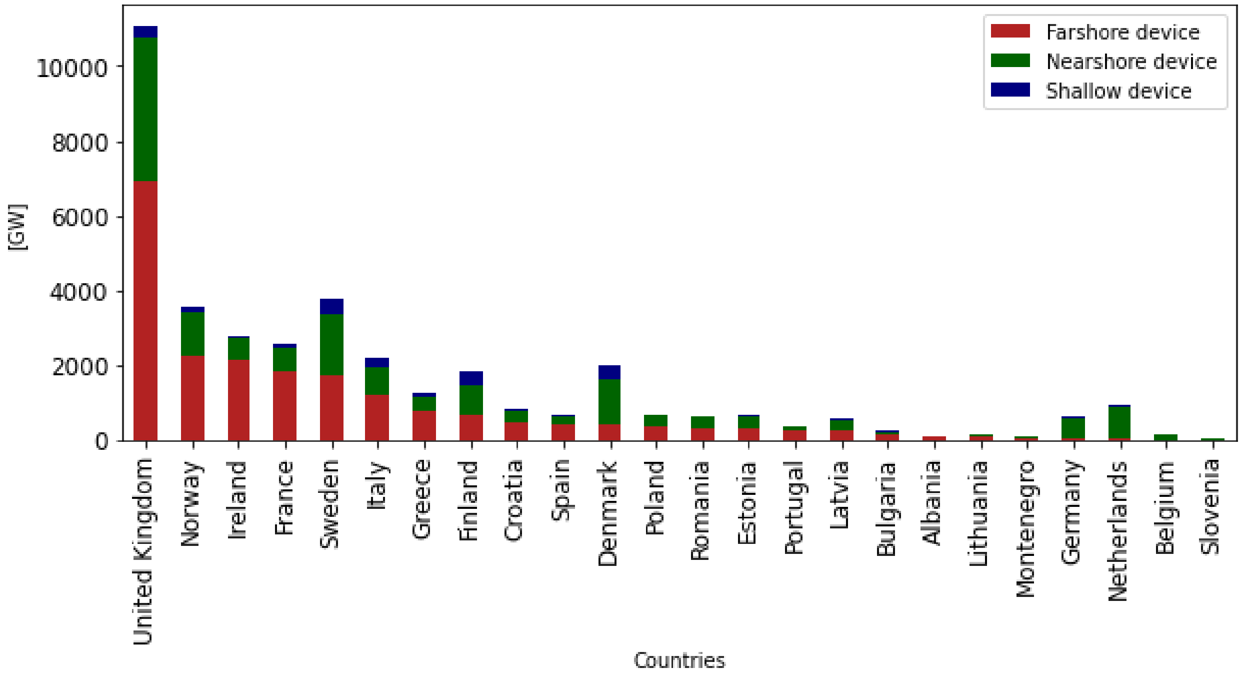

Figure 4.3 Maximum installable capacity of aggregated WEC devices by countries

Nonetheless, the geographic potentials do not provide the full picture, as they do not account for the wave resource availability, only representing eligible areas where WECs can be installed. To account for resource availability, and create the generator layout used in the optimization, the model computes the resource availability time series per unit of nominal capacity at each location. Allowing to compute the average capacity factor for the year 2018, based on the characterized sea states for every cell and time step, visualized in the second plot of each device in Figure 4.1 and Figure 4.2. The different average capacity factors of eligible geographic locations are presented. The highest capacity factors for the Farshore device for the year 2018 are found around the United Kingdom, including the Atlantic Ocean, north of the North Sea, as well as the Norwegian Sea on the coast of Norway, with a range between 20% and a maximum of 31%.

Meanwhile, a nearshore device in the year 2018 would showcase average capacity factors above 25% if placed on coasts north of the United Kingdom towards the North Atlantic Ocean, while also highlighting certain spots in the Celtic Sea. For a shallow device, although more restricted by land and depth eligibility, showcases capacity factors above 30% in various coastlines of Europe, highlighting coastlines across the North Sea including The Netherlands, Denmark, United Kingdom, as well as the Norwegian Sea, and the border of the Cretan Sea.

The power generation potential, also shown in Figure 4.1 and Figure 4.2, was derived by multiplying the geographical capacity potential times the yearly average capacity factor and the 8,760 hours in a year. This estimate provides insights on electricity generation potential as well as exhibiting locations with both extensive land availability and highly production sites. The North Sea appears as the most promising location, particularly for the Farshore and Nearshore device, although some regions around Denmark, including the Baltic Sea, appear to be attractive for the Shallow Device. Given this, the total maximum power generation potential during the year 2018 across all of Europe is estimated at 23,840 TWh for the Farshore device, 9,642 TWh for the Nearshore device, and 2,533 TWh.

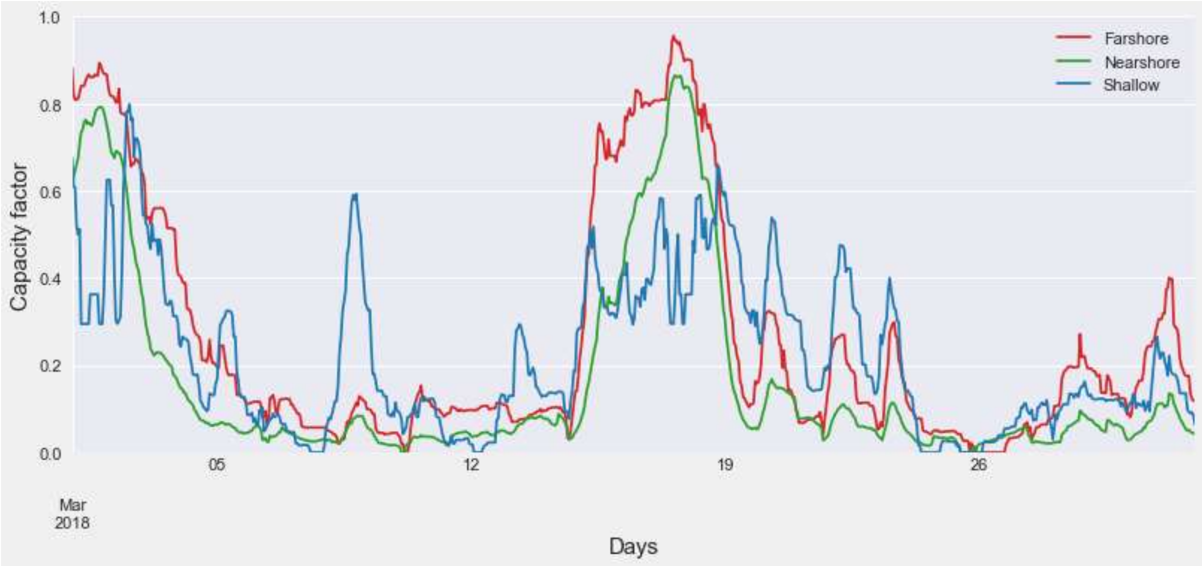

Figure 4.4 Exemplary country-aggregated (one node) availability time Series for WEC devices in The Netherlands, March 2018

Additionally, Figure 4.4 showcases an illustrative example of the country-aggregated power availability time series for the month of March 2018 computed by the model according to the metocean conditions for the three types of devices in The Netherlands. Within the model, the cutout consists of grid cells of certain resolution (approx.. 30km x 30 km), with each having its own weather timeseries. In parallell, network nodes are associated with geographical regions, in this case a one node per country region, which serve as catchment areas for electric loads, renewable energy potentials, and aggregation of the time series availability factor. To generate the country-aggregated availability time-series, the model first computes a capacity layout which specifies which grid cells of the cutout contain what potential amount of capacity of each generating technology. To compute this capacity layout, the geographic potential is multiplied by the capacity factor at each grid cell, following the logic to install more generators at cells with a higher capacity factor and higher land availability. This is followed by the model computing the power generation data for each grid cell and aggregating them to nodes or to the geometrical shapes (countries) by creating an indicator matrix which represents the spatial overlap of each cutout grid cell with each country/region shape. (Hofmann et al., 2021; Hörsch et al., 2018a) The figure demonstrates the daily and weekly variation of wave generation at an aggregated country level for The Netherlands.

4.2 Other renewables

On purely land availability criteria, the wave energy resource is the most abundant within Europe, especially in coastline countries. The wave resource has the highest geographic potential reaching approximately 20.3 TW. Figure 4.5 Figure 4.6, below, showcases the estimated geographic potential of a renewable resource and its distribution across Europe and by each country.

Furthermore, significant differences in the magnitude of available technical potential or energy can be observed between landlocked and coastal countries, driven by both the wave energy and the offshore wind resource. Another, point to note is that the resource potential of run-off rivers and hydro is constant and not affected by Climate Change, however, this, in reality, will not occur as studies have shown that decreases are expected (DOE, 2017).

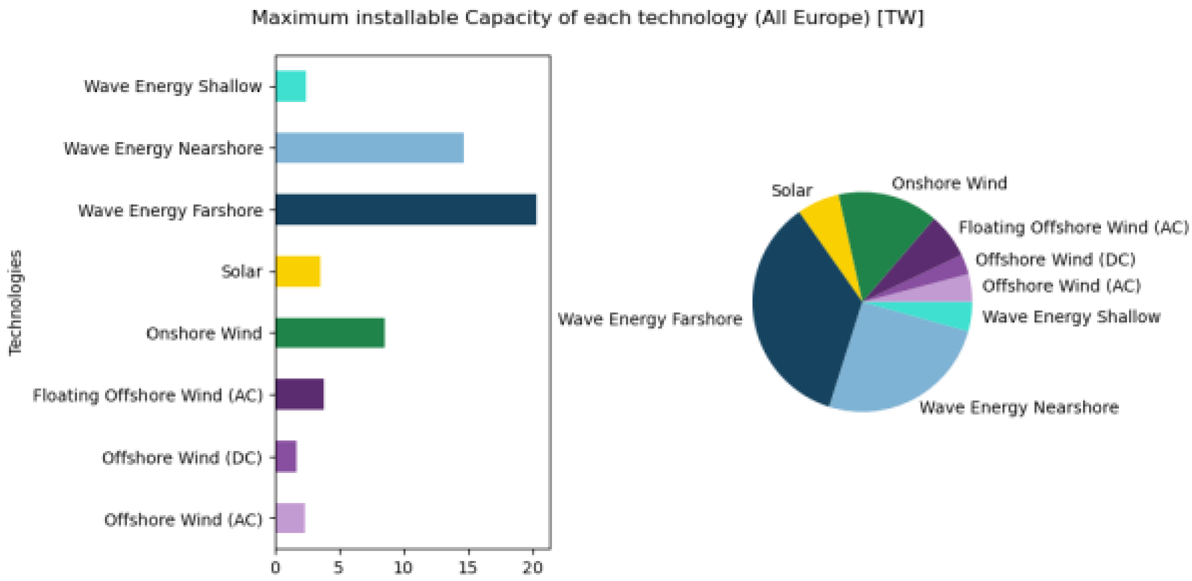

Figure 4.5 Installable geographic potential and distribution for the whole of modeled Europe

Caution is needed while interpreting these figures, as the geographical potentials of each renewable resource can be under conditions aggregated. This is due to the fact that resources may share eligibility criteria for a certain region, such as offshore wind and wave energy, which can be combined. However, in the case between the Farshore and nearshore wave energy devices, where regions with water depths between 50 and 80 m are eligible for both devices, capacities are not aggregated as they will depend on sitting conditions.

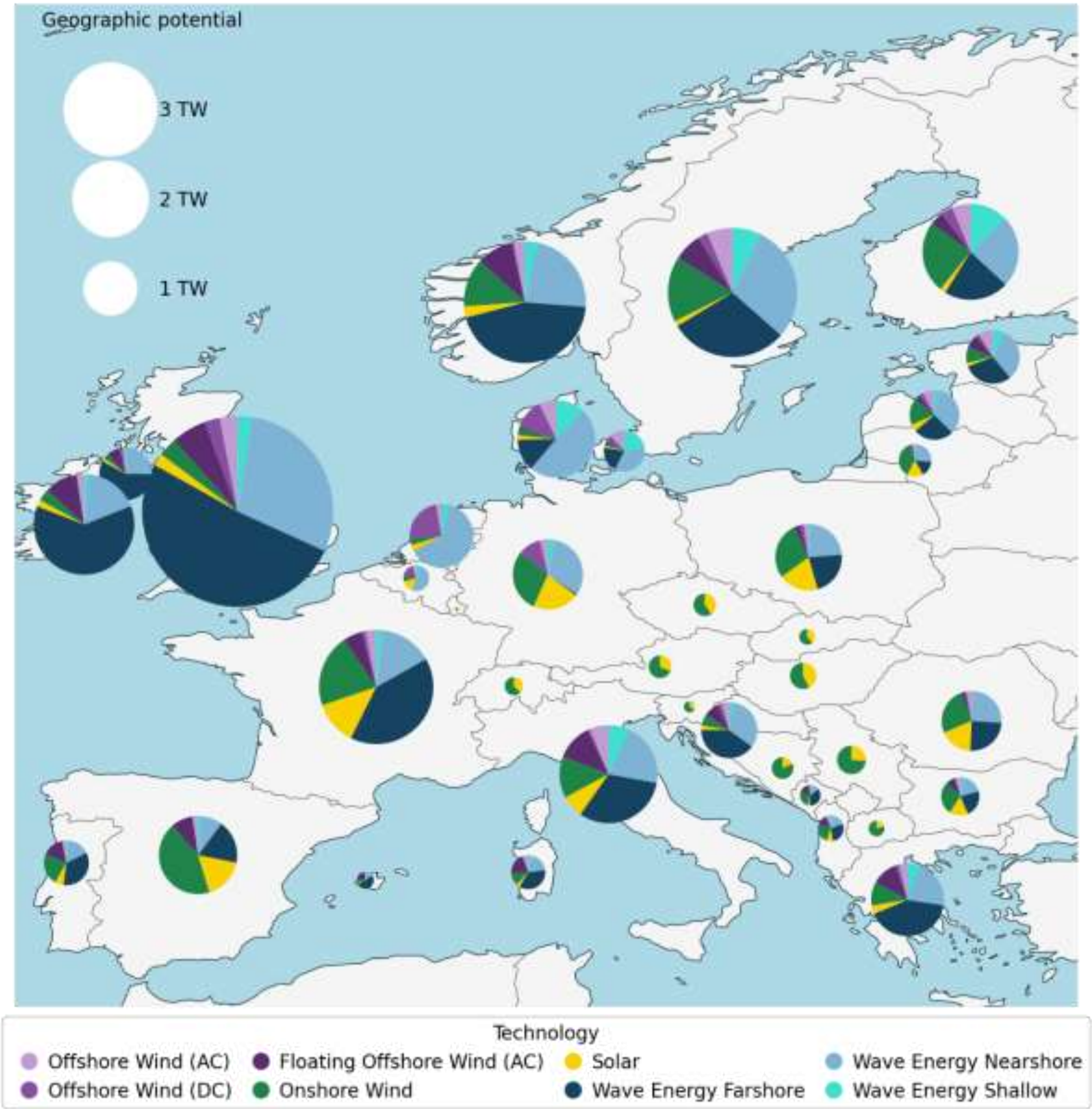

Figure 4.6 Installable geographic potential distribution of renewable technologies by country, Europe 2018

4.3 Development trajectory scenarios

The upgraded PyPSA-Eur model was executed under 100% renewable scenarios with 2030, 2040, and 2050 horizons under 2018 weather conditions considering increases in demand based on historical trends and capacity expansion constraints described in section 3.4.3. The model assessed and optimized the deployment of solar, onshore & offshore wind (bottom-fixed and floating), and three different wave energy generators under a simplified network topology. The results of the model and scenarios are presented below.

4.3.1 Network simplification

As explained in section 2.4.4.4, the model network is simplified for all scenarios. This is due to the fact that modeling the whole European transmission system at full resolution is a complex task that could not be solved with the available resources at a reasonable time. The network resolution was simplified, using a k-means network clustering algorithm, to 37 nodes within 33 countries (countries like Denmark are part of two synchronous zones, thus two nodes are modeled). Figure 4.7 visualizes the network simplification. After clustering, the network has 52 High Voltage Alternating Current (HVAC) lines, shown in red, and 37 High Voltage Direct Current (HVDC) lines. The largest aggregated transmission line has a capacity of 27.17 GW and is located between Switzerland and Germany.

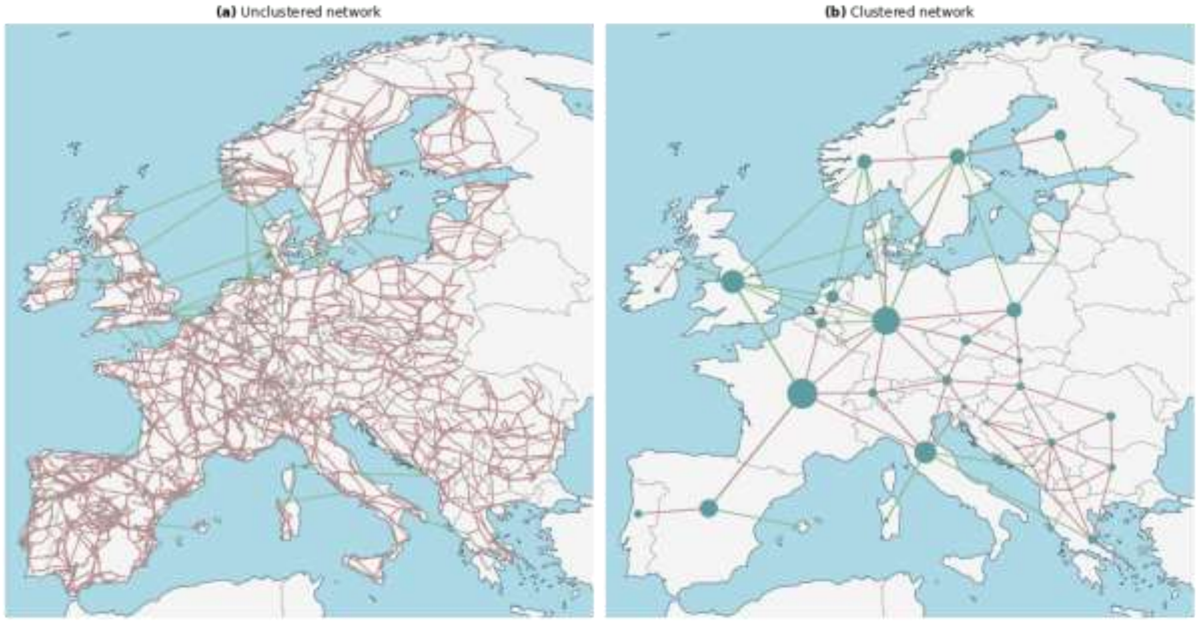

Figure 4.7 (a) Network topology imported from the ENTSO-E Transparency data 2019. (b) European transmission network clustered to 37 nodes.
Notes: Red lines represent HVAC connections while green lines represent HVDC connections. Blue circles represent the network nodes, and their size represents the load distribution at a specific snapshot.

It is important to mention that although network simplification allows to simplify the problem complexity and reduces the computational time and resources to solve it, reducing the spatial resolution can have strong effects on modeling results, particularly by underestimating total system costs because it can ignore bottlenecks in the system (Frysztacki et al., 2021a).

4.3.2 Electricity Demand

As mentioned in section 2.4.4.3, data on electricity consumption in the model is obtained from historical data from ENTSO-E statistics using 2018 as the reference year. Given that the development scenarios are modeled at the time horizons of 2030, 2040, and 2050, consumption data of the reference year was multiplied by global scaling factors estimated according to the methodology described in section in section 3.4.3.1.

The global scaling factors applied to the scenarios 2030, 2040, and 2050 were 1.10, 1.19, and 1.28, respectively over the 2018 reference year. The resulting total load for each development trajectory scenario is shown in Table 4.2. Meanwhile, the hourly profile for each scenario is presented in Figure 4.8. The total electricity consumption in the 2050 Network represents an increase of 16% against the modeled 2030 network and a 7.5% increase over the 2040 network. Meanwhile, the 2040 network represents an 8.1% increase over the 2030 network.

Table 4.2 Total electricity consumption in the modeled network for each scenario

2030 Network	2040 Network	2050 Network
3628.7 TWh	3925.6 TWh	4222.5 TWh

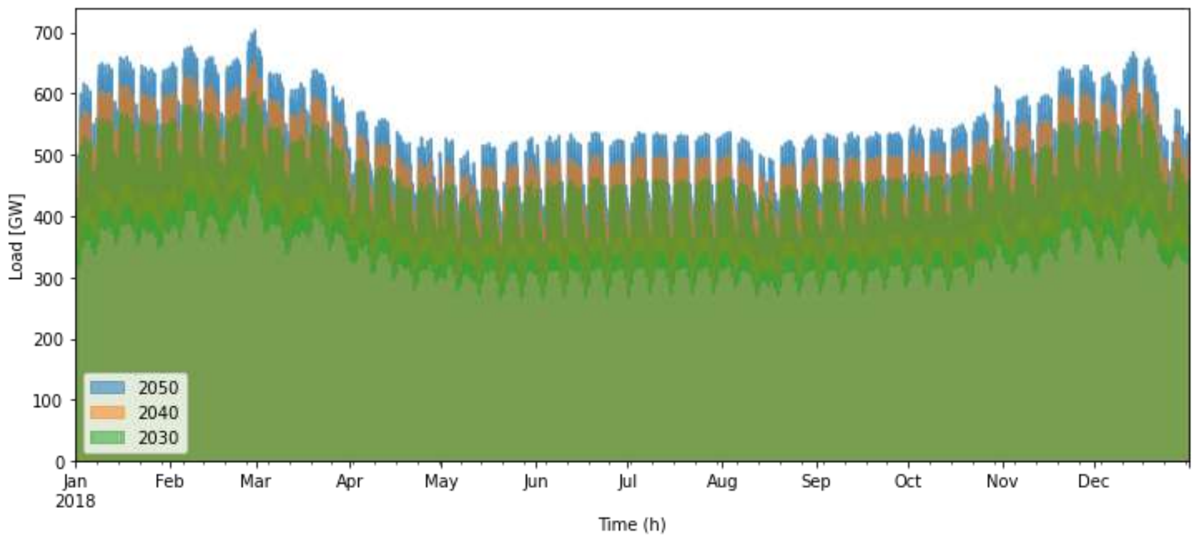

Figure 4.8 Hourly load profile for each development trajectory scenario

4.3.3 Generation

For each scenario, a future, 100% renewable European Electricity network was modeled via a greenfield optimization. The European power system was built from scratch, except for existing hydroelectric and geothermal capacities, which are not extendable during the optimization and remain with a fixed capacity. For other renewables and storage technologies, the installed capacities and their respective dispatch at every time step are optimized depending on the geographical and weather-dependent potentials. The optimized capacity of each type of generator for each of the development trajectory scenarios is summarized in Table 4.3 and visualized in Figure 4.9. Meanwhile, Table 4.4 showcases the annual electricity production by technology for each of the development trajectory networks.

Table 4.3 Optimized capacities of renewable generators for each development trajectory network [GW]

Carrier	2030	2040	2050
Solar	1146.9	1212.9	1273.2
Onshore Wind	1076.4	1161.3	1267.6
Reservoir & Dam	99.6	99.6	99.6
Run of River	34.5	34.5	34.5
Offshore Wind (DC)	11.7	9.6	11.9
Geothermal	0.8	0.8	0.8
Wave Energy Shallow	0.01	26.37	30.97
Offshore Wind (AC)	0.011	0.013	0.016
Floating Offshore Wind (AC)	0.004	0.008	0.009

Wave Energy Nearshore	0.003	0.005	0.009
Wave Energy Farshore	0.002	0.003	0.005
Total	2370	2545	2719

Table 4.4 Annual electricity generation of optimized renewable generators for each development trajectory network [TWh]

Carrier	2030	2040	2050
Onshore Wind	2010.5	2216.8	2447.1
Solar	1428.6	1517.8	1604.0
Reservoir & Dam	343.8	343.8	343.8
Run of River	125.4	125.5	125.5
Offshore Wind (DC)	33.0	26.9	32.4
Geothermal	7.1	7.1	7.1
Offshore Wind (AC)	0.024	0.027	0.034
Wave Energy Shallow	0.012	30.756	36.018
Floating Offshore Wind (AC)	0.009	0.017	0.020
Wave Energy Nearshore	0.001	0.002	0.004
Wave Energy Farshore	0.001	0.002	0.003
Total	3948	4269	4596

Solar PV is the dominant technology installed in terms of capacity in the cost-optimal configurations of the 100% renewable power system, with 1,146 GW and representing 48.4% of the total capacity installed in the 2030 network and 46.8% in the 2050 network with 1,273 GW. Nonetheless, onshore wind is the dominant technology in terms of electricity generation, as seen in Table 4.4, reaching over 2000 TWh through all networks. This highlights that even though the installed capacities of Solar and onshore wind are similar, the higher availability of supply from wind translates to increased electricity generation.

The decrease in the share of solar through the development trajectories does not imply a decrease in capacity installed, as seen in Table 4.3. In terms of capacity, Solar PV is followed by Onshore wind, which has a total capacity share of 45.4% with 1,076 GW installed in 2030 and an increase of capacity up to 1,267 GW in 2050 with a capacity share of 46.6%.

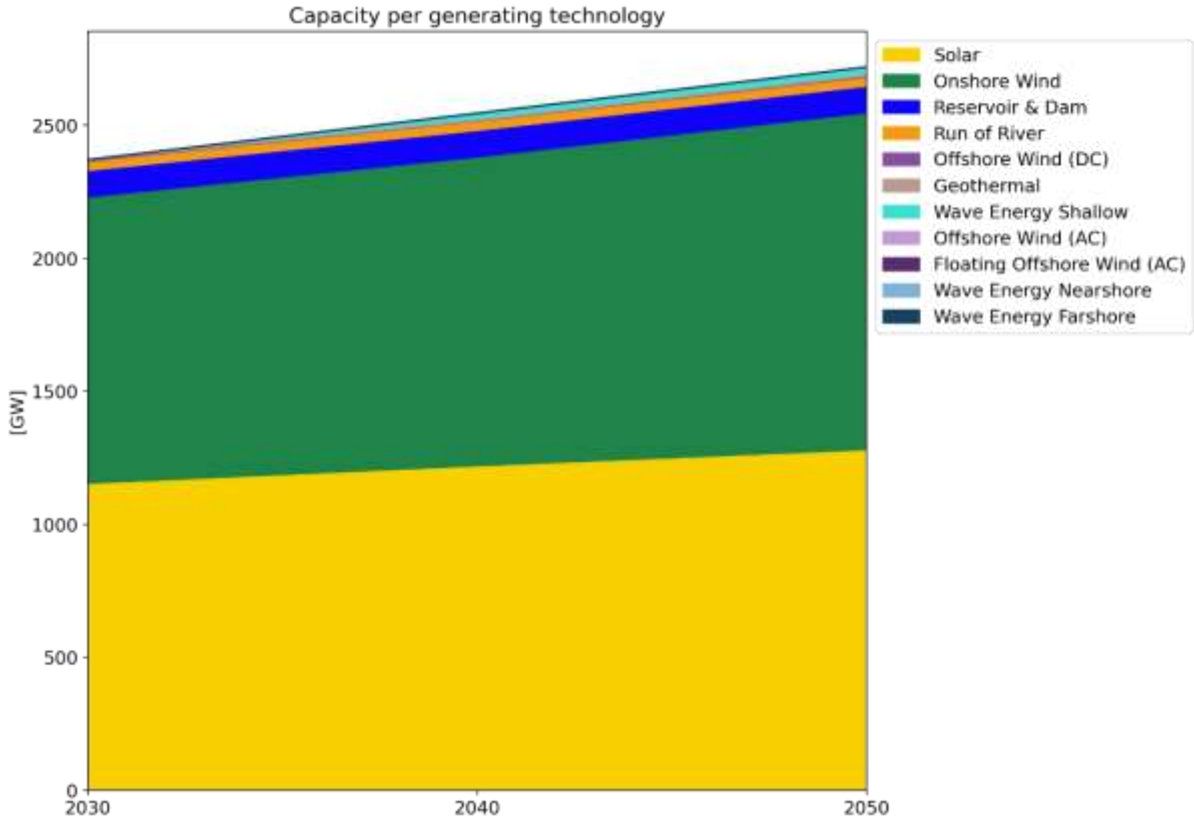

Figure 4.9 Optimized capacities of renewable generators across the development trajectory networks

Furthermore, Figure 4.10 presents how the installed capacity of each technology evolves across the different horizons of the scenarios. The installed capacity of all technologies increases across the different time horizons with the exception of the non-extendable generators (geothermal, reservoir& dam, and run of the river) and interestingly offshore wind (DC). The latter showcases a reduced installed capacity from 11.74 GW in 2030 to 9.62 GW in 2040, representing an 18% reduction. In 2050, 11.8 GW of offshore wind are installed, marginally above the installed capacity in 2030.

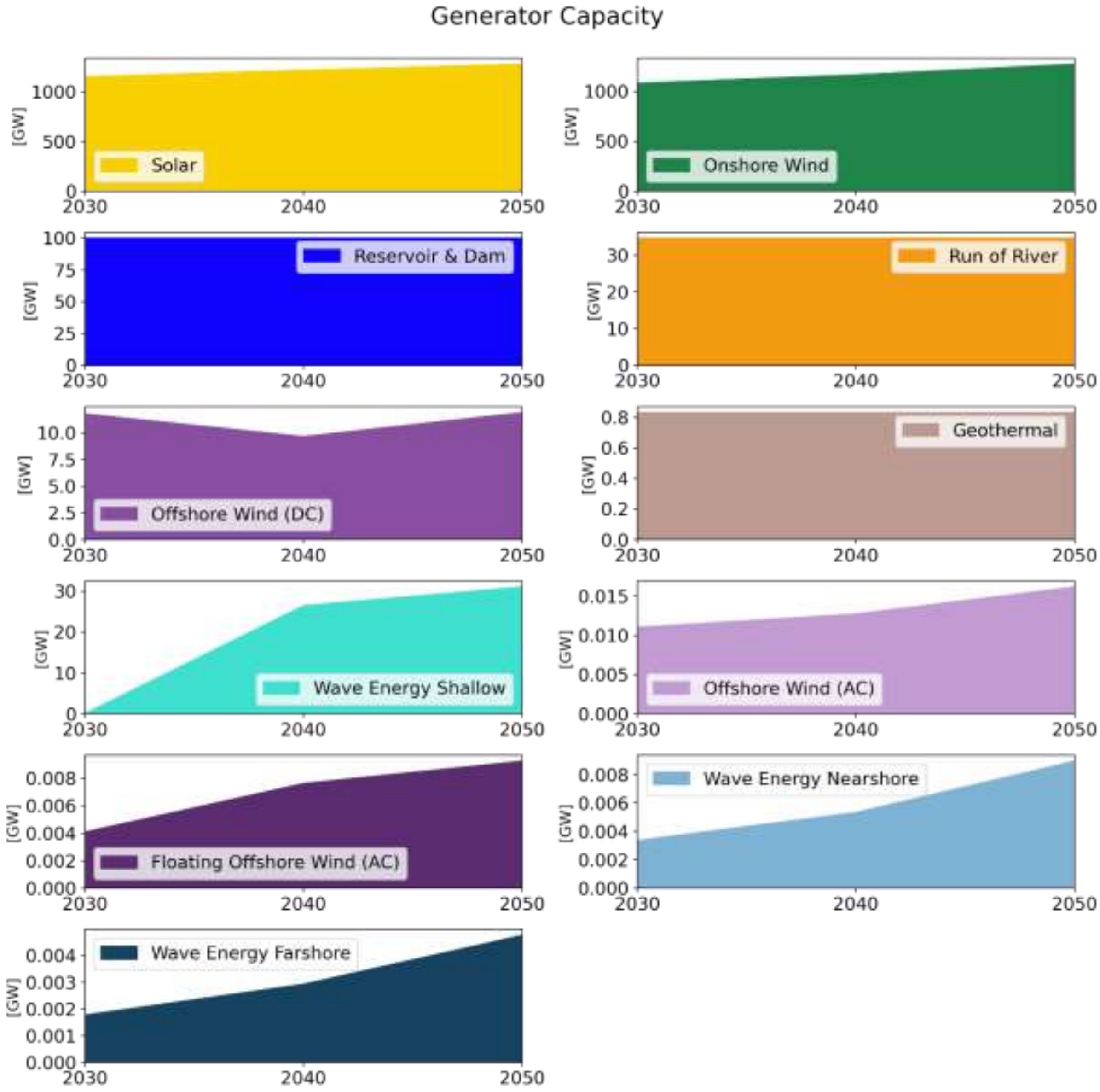

Figure 4.10 individual capacity of renewable generators across the development trajectory networks

The shallow WEC device is the generator with the greatest rate of increased capacity, going from only 12 MW in 2030, to 26.3 GW by 2040 and reaching 30.97 GW in 2050. Thus, the capacity installed in 2040 is almost 2,200 times the installed capacity in 2030, while a 17% increase is observed from 2040 to 2050. It can be assumed that the main driver for this increase is the capital cost reduction of the device inputted in the model, however, further analysis of the drivers and locations where it is installed can be found in the discussion section

For the other WEC devices, an increase in installed capacity is also observed but not at the same level of magnitude. Almost 2 MW of the Farshore device are installed in the 2030 network, with a 50% increase in capacity reaching 3 MW by 2040 and 5 MW by 2050. In the 2030 network, 3 MW of the WEC nearshore device are installed, followed by a 67% increase in capacity reaching 5MW by 2040, and by 2050 a 200% increase is observed compared to the 2030 installed capacity reaching 9 MW.

Interestingly, while the resulting cost-optimal wave energy cumulative capacity of 17 MW in the 2030 network comes for the European Commission's 1 GW target of ocean energy by 2030 outlined in the EU's offshore energy strategy (European Commission, 2020a), the resulting cumulative wave energy capacity of 30.9 GW in the 2050 network is very much in line with the 2050 target of 40 GW of ocean energy. Especially considering that this target considers other technologies such as tidal, floating offshore wind, and solar.

Figure 4.11 showcase the European distribution of installed capacity across the networks with different time horizons. The dominance of the mature renewables solar PV and onshore wind is observed for all networks. These two technologies account for 93.8% of the installed capacity for network 2030, 93.3% for network 2040, and 93.4% for network 2050. The third technology with the most capacity is hydroelectric generation, with a fixed capacity in all scenarios of 99.562 GW, representing between 4.2% of installed capacity in 2030 and 3.7% in 2050. Nonetheless, wave energy shallow, with its 30.9 GW of installed capacity by 2050, achieves a 1.14% share of the generator mix in that year.

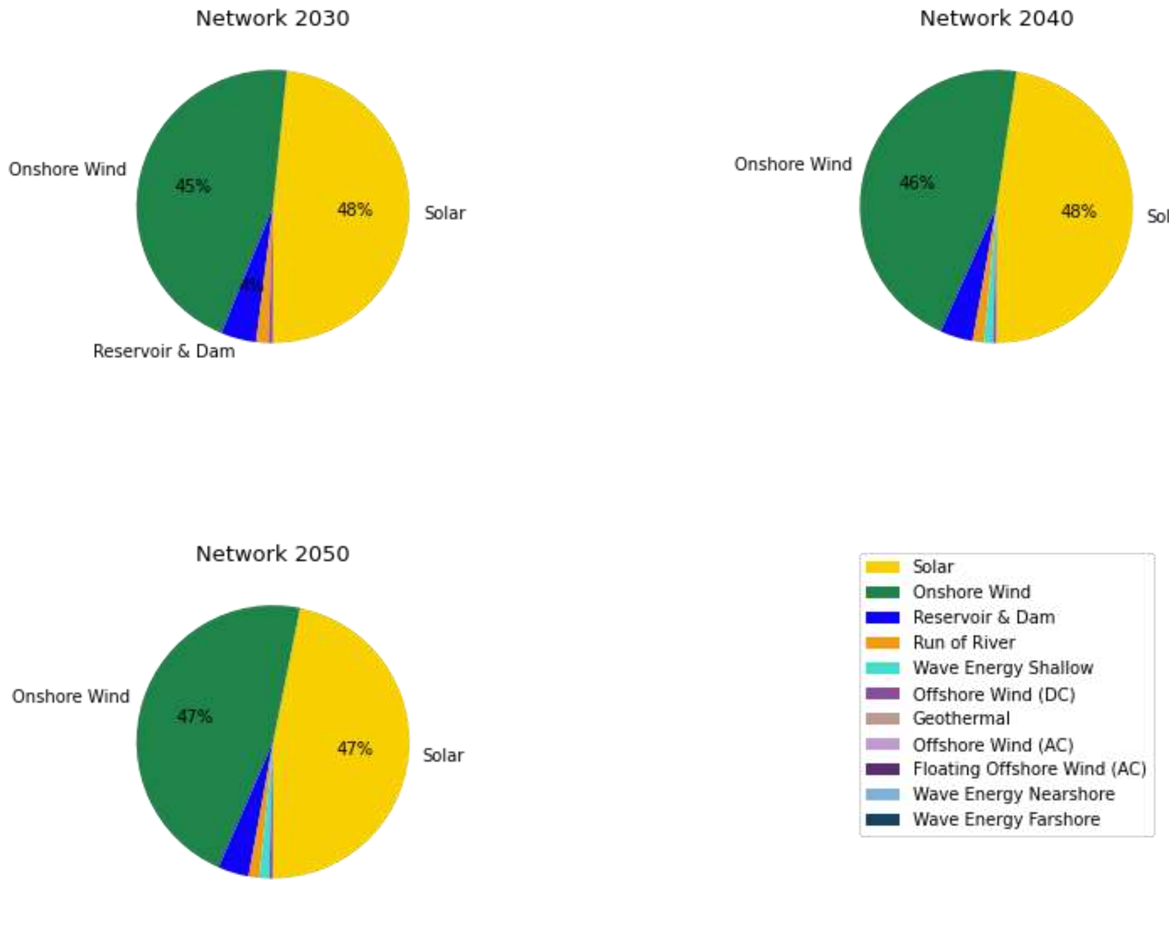

Figure 4.11 Distribution of capacity by renewable generator for all development trajectory networks

To better understand the distribution of the technologies it is necessary to analyze where these technologies are deployed. Figure 4.12 showcases the distribution of installed solar and onshore wind across Europe for the 2050 Network. It can be observed that both mature technologies are widely installed across different states. Solar is mainly installed in Western and Southern Europe, with Italy, Germany, France, and Spain accounting for 57.64% of the 1273.2 GW of installed solar Europe-wide. Meanwhile, onshore wind is more distributed across the countries with coastlines, with France being the country with the most installed capacity (22.8% of the total), but also including the United Kingdom (21.63%), and Poland (13.8%).

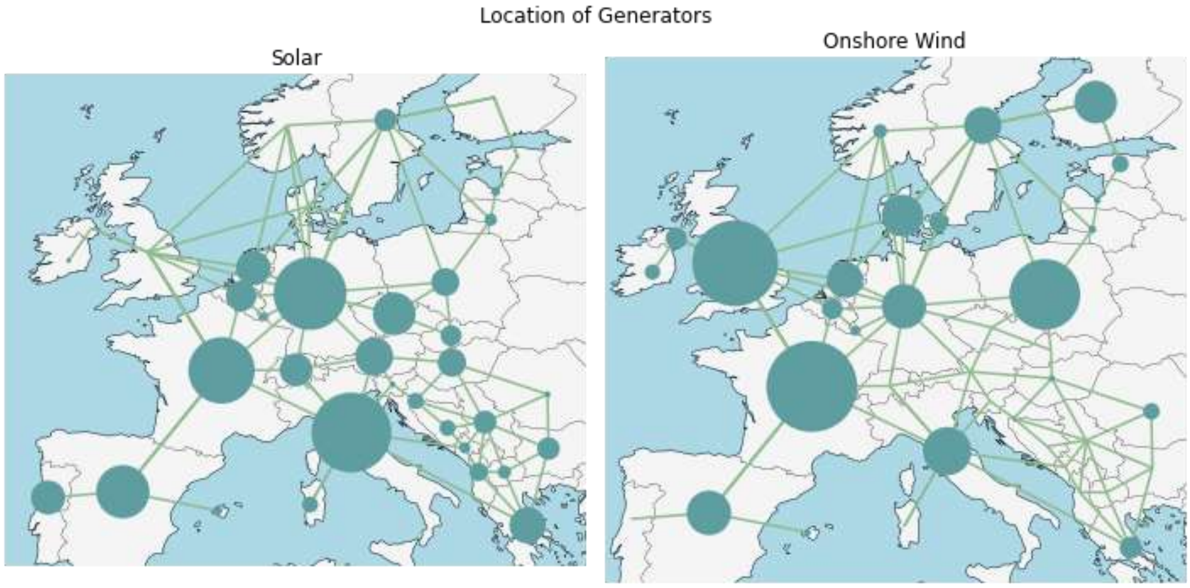

Figure 4.12 Distribution of installed solar and onshore wind, Network 2050.
Total installed solar: 1273.2 GW, largest node: 252.4 GW (Italy)
Total installed onshore wind: 1267.6 GW, largest node: 289.7 GW (France)

Wave energy shallow and offshore wind (DC) are the offshore technologies with the highest installed capacity in the 2050 network, with 30.97 GW and 11.85 GW, respectively. Figure 4.13 showcases the distribution of these technologies. 99.9% of installed offshore wind (DC) is in Romania, in the Black Sea. Although not observed in the figure, the remaining 12 MW of offshore wind (DC) are installed in Denmark, Poland, Lithuania, Latvia, and the United Kingdom.

For wave energy shallow, most of the capacity is distributed across South Eastern Europe and the Italian island of Sardinia. More specifically 37.3% of the total 30.97 GW of installed wave energy shallow is installed in Albania, between the Adriatic and the Ionian Sea. Meanwhile, 40.3% is installed in the Black Sea between Bulgaria (31.9%) and Romania (8.4%), and 22.4% around the island of Sardinia, in the Mediterranean Sea.

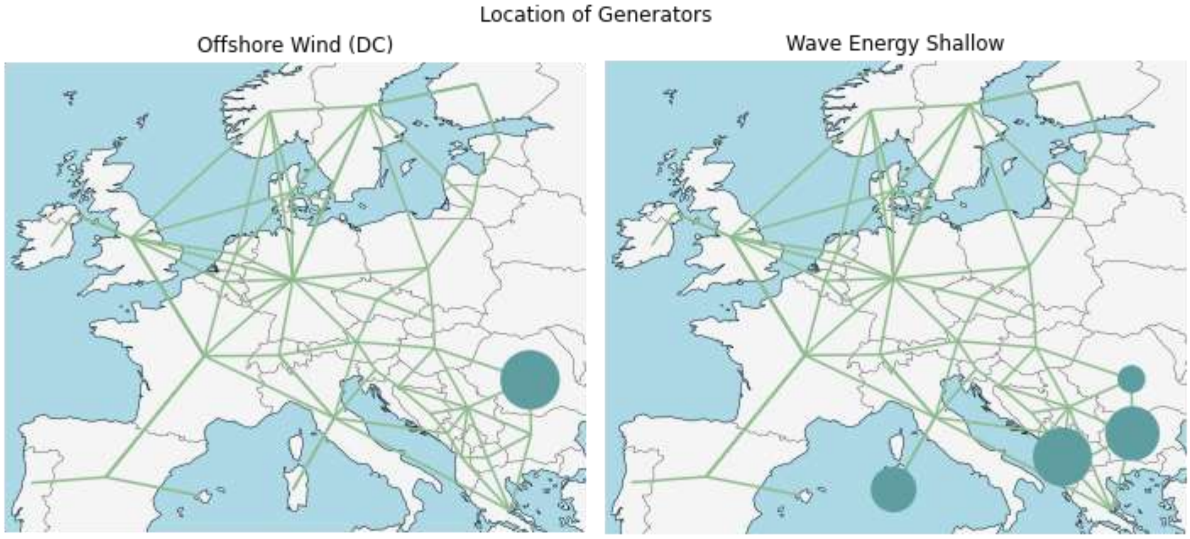

Figure 4.13 Distribution of installed offshore wind (DC) and wave energy shallow, Network 2050.
Total installed offshore wind (DC): 11.85 GW; largest node: 11.84 GW (Romania)
Total installed wave energy shallow: 30.97GW; largest node: 11.55 GW (Albania)

Other offshore technologies are not significantly deployed across Europe as only a cumulative 40 MW of these technologies are installed. 16.1 MW of offshore wind (AC), 9.2 MW of Floating offshore wind, 8.9 MW of wave energy nearshore, and 4.7 MW of wave energy farshore are installed across Europe's coastlines. Figure 4.14 showcases the distribution of these remaining offshore technologies.

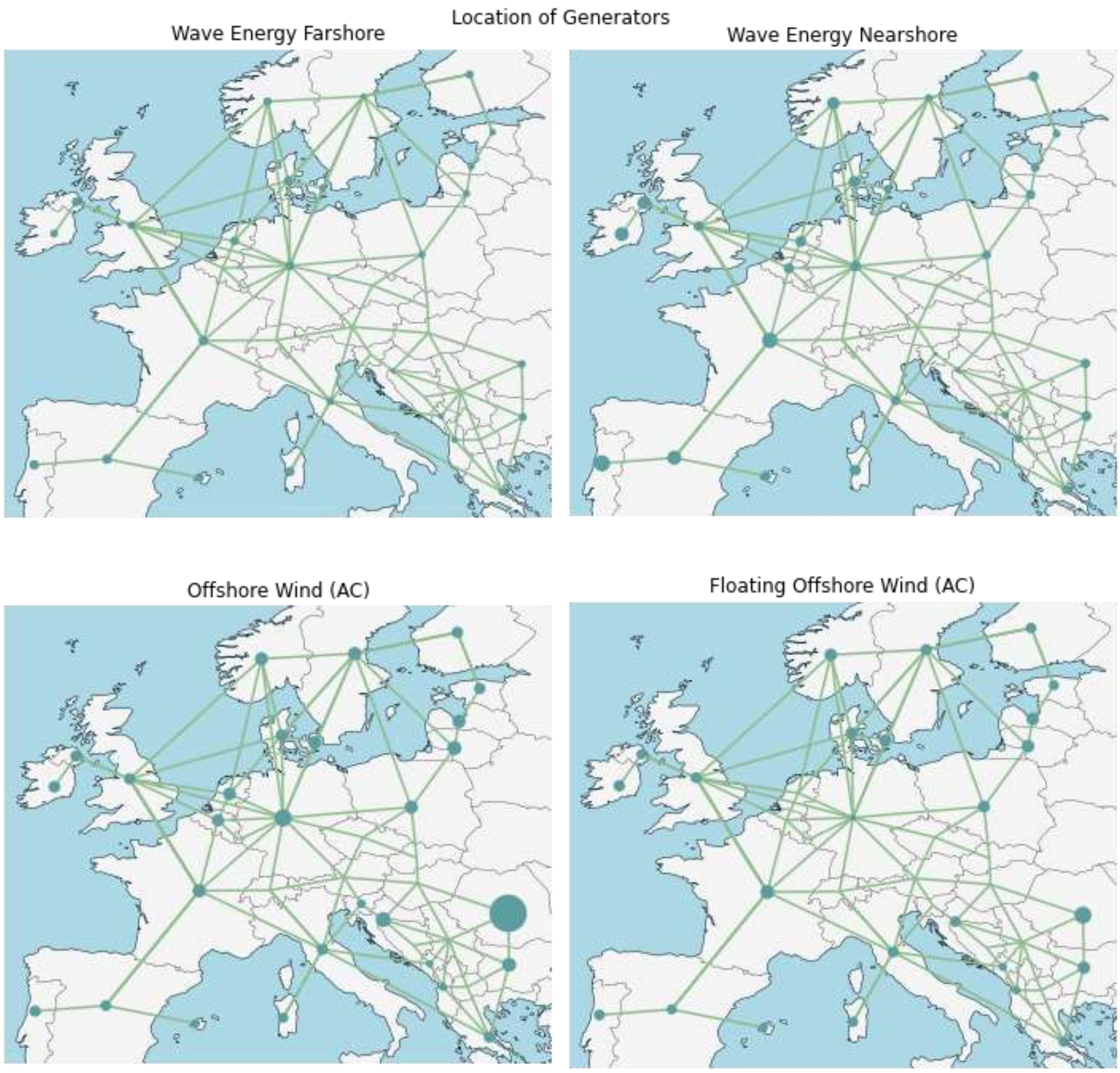

Figure 4.14 Distribution of installed wave energy farshore, wave energy nearshore, offshore wind (AC), and floating offshore wind, Network 2050.
Total installed wave energy farshore: 4.7 MW; largest node: 0.48 MW (Spain)
Total installed wave energy nearshore: 8.9 MW; largest node: 0.74 MW (Portugal)
Total installed offshore wind (AC): 16.1 MW; largest node: 4.16 MW (Romania)
Total installed floating offshore wind: 9.2 MW; largest node: 0.85 MW (Denmark)

To further analyze the resulting cost-optimal configurations of the modeled system across the development trajectory networks, the generation capacity by country as well as the country's technology mix for network 2030, network 2040, and network 2050 is shown in Figure 4.15, Figure 4.16, Figure 4.17, respectively. Furthermore, the results are also shown in the appendix in Table 8.1, Table 8.2, and Table 8.3

In all three of the cost-optimal configurations of the networks under different horizons, France and Italy are the countries with the greatest amount of installed capacity. France's installed capacity ranges from 406.9 GW (17.2% of total installed capacity) installed in 2030 to 472.4 GW (17.4% of total installed capacity) in 2050. Of the total installed capacity in France in network 2030, 63.1% is onshore wind and 33.3% Solar PV, while in network 2050 a 61.3% share represents onshore wind and 35.6% Solar PV.

Onshore wind and solar also dominate the Italian technology mix representing a combined 96.3% share of installed capacity in 2030 and 94.76 % in 2050. Nonetheless, solar is the dominant technology across Italy, with a 73.4% share of the 314.4 GW installed in 2030 and 71.6% of the 352.6 GW installed in 2050.

Interestingly, the United Kingdom and Denmark are powered almost exclusively by onshore wind. For the United Kingdom, onshore wind represents 99.2% of the 175.3 GW installed in 2030 and 99.6% of the 275 GW installed in 2050. Furthermore, the country exhibits high capacity additions between the different horizons, where the 220.7 GW installed in 2040 represent a 25.9% increase over the capacity installed in 2030. For 2050, an additional 54.6 GW of generating capacity, almost exclusively onshore wind, is installed over the 2040 network, representing 24.8% over a decade. Meanwhile, Norway's power mix is dominated by existing non-extendable hydroelectric (Reservoir & Dam) capacity, representing 82.2 of its generating mix.

On the other end of the spectrum, small countries like Luxemburg and countries in Eastern Europe are the ones with the least installed capacity. These include Montenegro, Slovenia, and Latvia. Interestingly, Solar PV in Slovenia varies across the different networks, with 4.2 GW of solar (72.6% of its technology mix) in the 2030 network, which is almost nonexistent in the 2040 network, with only 21.8 MW of installed solar. While for the 2050 network, 1.3 GW of solar are installed. The technology mix for each country, as well as the installed capacities of each technology, are visualized in Figure 4.15, Figure 4.16, and Figure 4.17. The results can also be found in Table 8.1, Table 8.2, and Table 8.3 in the Appendix.

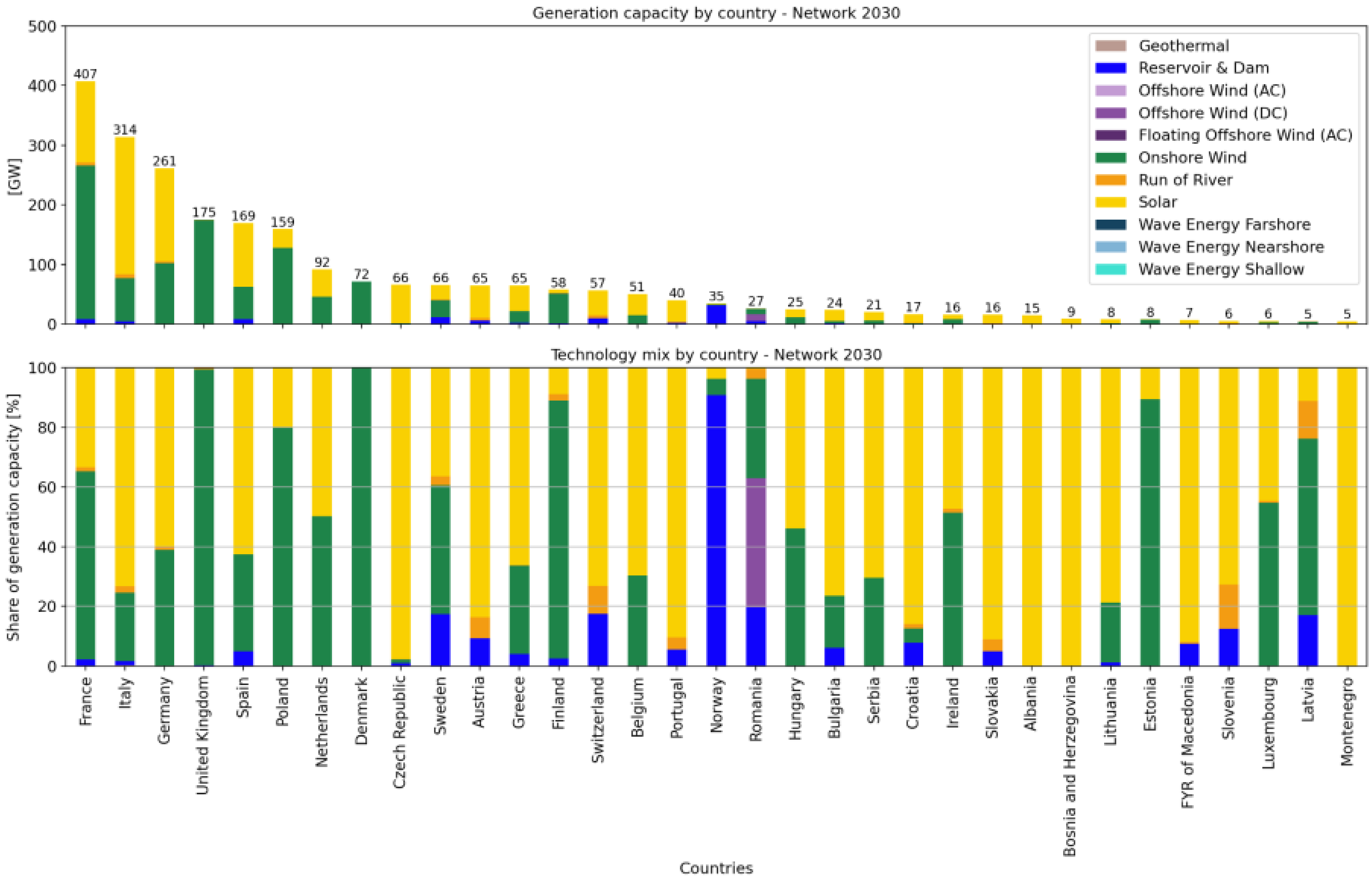

Figure 4.15 Optimal installed capacities and technology mix for each country, Network 2030. Corresponding results are presented in Table 8.1 in the Appendix.

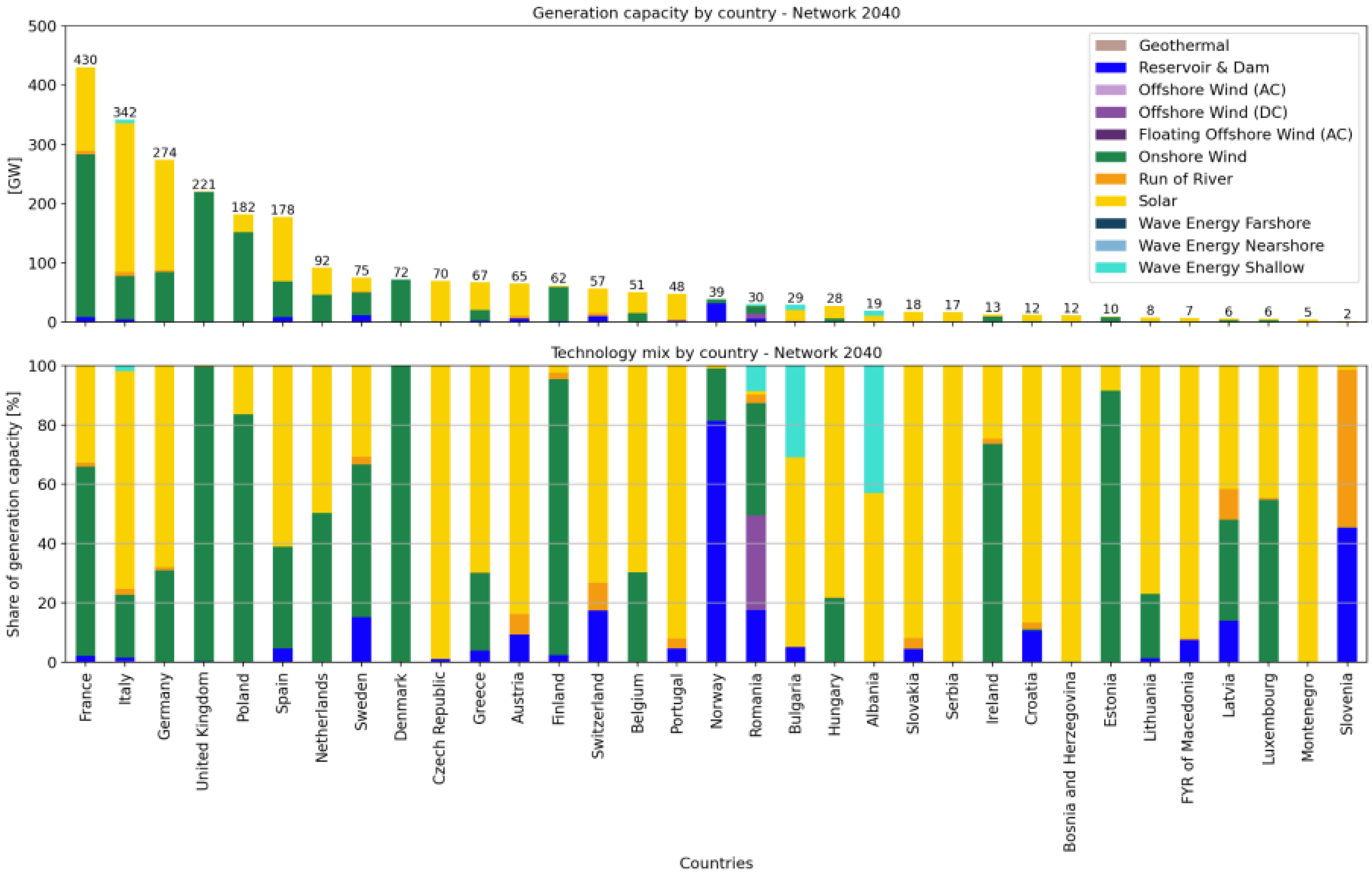

Figure 4.16 Optimal installed capacities and technology mix for each country, Network 2040. Corresponding results are presented in Table 8.2 in the Appendix.

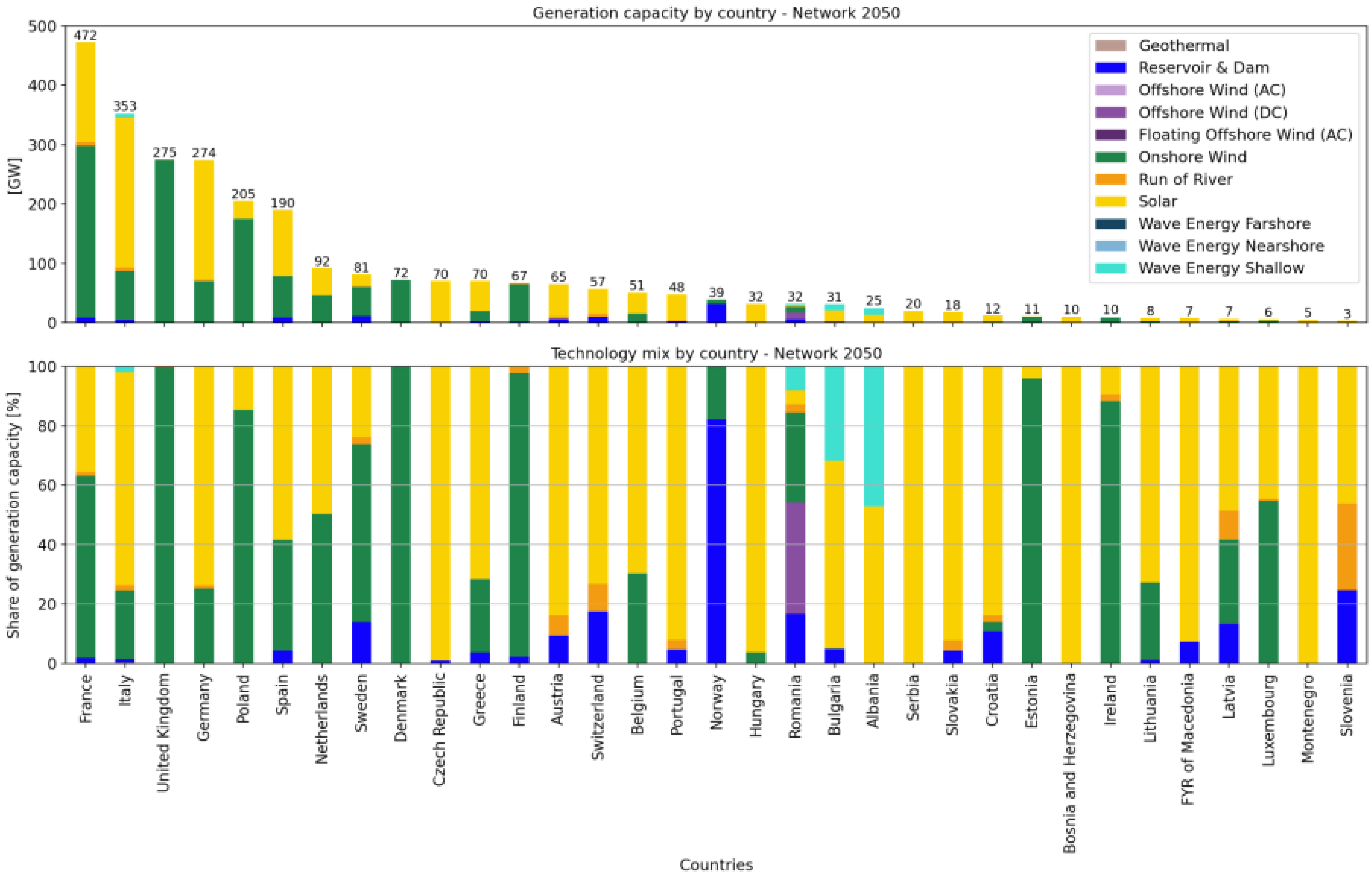

Figure 4.17 Optimal installed capacities and technology mix for each country, Network 2050. Corresponding results are presented in Table 8.3 in the Appendix.

4.3.4 Storage

Under the different development trajectory scenarios modelled of the future, 100% renewable European Electricity power system storage technologies were considered in the optimization. These technologies are used for inter-temporal power shifting. Battery storage, hydrogen storage, and pumped hydro storage (PHS) were the technologies included in the model. Battery storage represents the short-term storage used to balance variability on a day-to-day basis. Hydrogen storage is the long-term storage option for balancing seasonal variabilities. PHS is considered a non-extendable technology, and, like run-of-the-river and hydro-electric generators, its capacity is fixed exogenously according to existing capacities gathered through the PyPSA-Eur framework (Hörsch et al., 2018a) and remains fixed across the scenarios. Within the model, storage energy capacities are assumed to be proportional to the nominal power capacities, with the energy-to-power ratio “Maximum hours” representing the time in which a storage unit can be fully charged or discharged at maximum power. The maximum hours for battery storage is 6 hours, hydrogen storage is set at 168 hours, and PHS has different maximum hours for different locations.

Table 2.1 summarizes the nominal power capacities of each type of storage technology for the cost-optimal configurations of the different development trajectory scenarios. PHS remains constant through the scenarios, while battery and hydrogen storage increase through the different horizons. Figure 4.18 visualizes how the power capacities of storage technologies evolve.

Table 4.5 Optimized capacities of storage technologies for each development trajectory network [GW]

Storage technology	2030	2040	2050
Battery Storage	141.38	151.40	161.10
Hydrogen Storage	132.60	143.92	158.61
Pumped Hydro Storage	54.59	54.59	54.59
Total	328.57	349.91	374.31

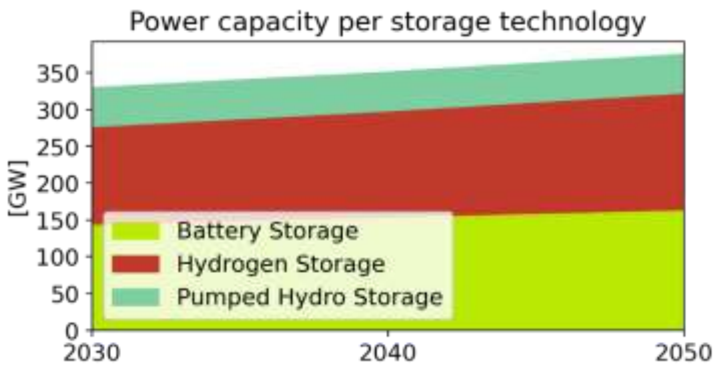

Figure 4.18 Optimized capacities of storage technologies across the development trajectory networks
Battery energy-to-power ratio: 6 hours
Hydrogen energy-to-power ratio: 168 hours
PHS energy-to-power-ratio is independent for every country

Hydrogen storage, with 141.38 GW installed in 2030 represents a 40% share of installed power capacity and increases its share to 42% with 132.6 GW in network 2050. While battery storage remains with a 43% share across all networks and PHS, despite maintaining a fixed power capacity, its share decreases from 17% in 2030 to 15% in 2050. Nonetheless, installed power capacity does not provide information on the amount of energy that can be stored. Given that the energy capacity is proportional to the nominal power capacities according to their respective energy-to-power ratios, Figure 4.19 showcases the European aggregated maximum amount of energy storage for each technology calculated as the nominal power capacity times its respective maximum hours. This plot showcases that hydrogen storage, as well as PHS, can store a relevantly higher amount of energy given their longer charging/discharging time.

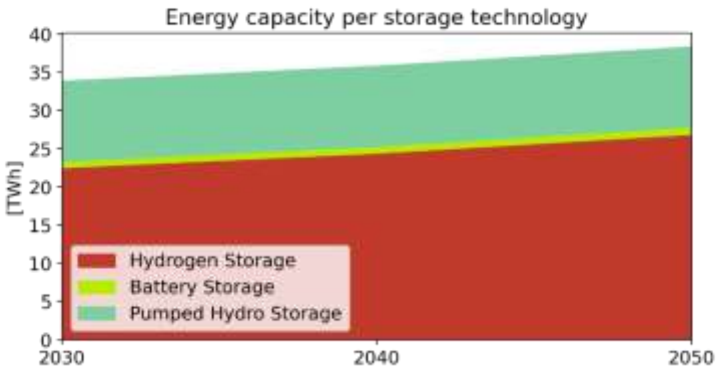

Figure 4.19 European aggregated energy capacity of storage technologies

Figure 4.20 plots the Europe-aggregated state of charge levels of the different storage technologies across the year. The aggregated state of charge level was calculated, for every storage technology, by dividing the sum of all stored energy among all countries by the sum of their maximum energy capacities (Maximum hours times nominal power capacity). The short and long-term roles of batteries and hydrogen can be observed in the Figure. Hydrogen storage and PHS energy levels vary across weeks and months, while the daily variation of battery is observed in the third plot of the Figure. The fourth plot showcases battery storage for the month of February, chosen as an example to depict with greater detail the hourly profile of battery storage.

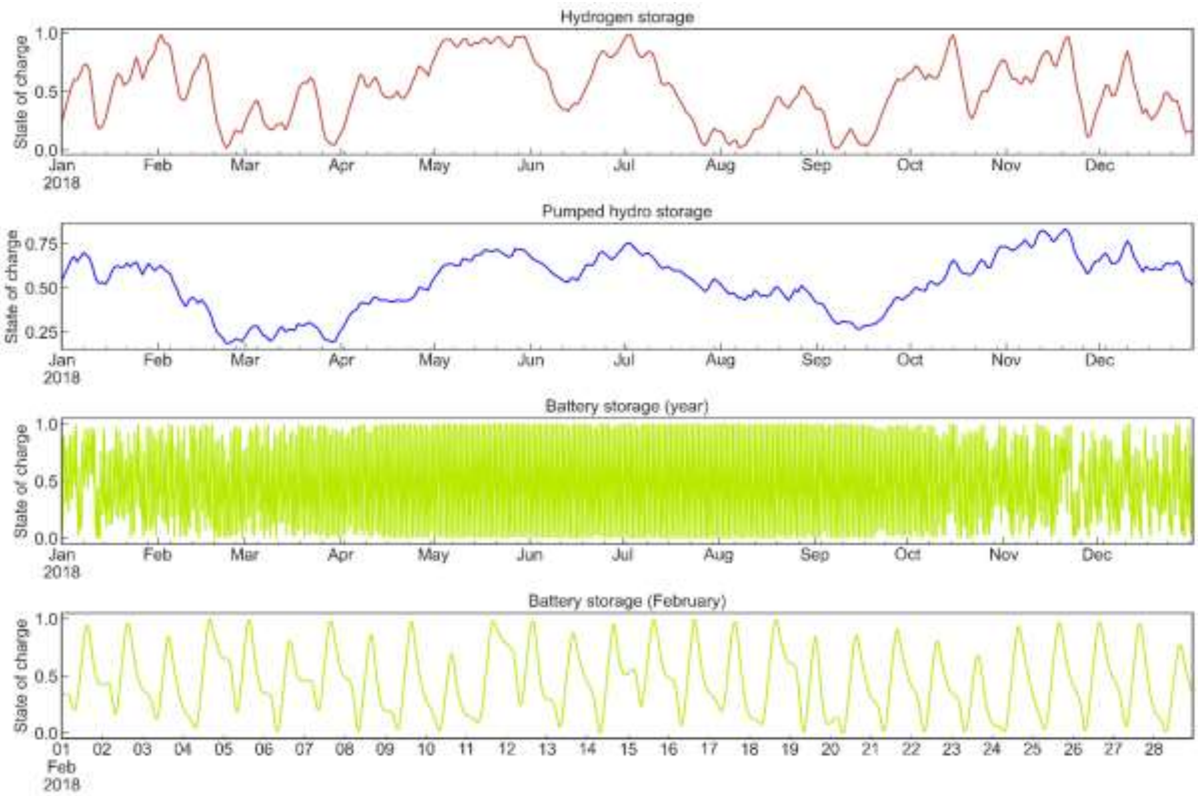

Figure 4.20 Europe aggregated state of charge of storage technologies, Network 2050.

To gain a better understanding of the distribution of storage technologies across Europe, Figure 4.21 shows the locations where each storage technology is installed. The size of the node represents the power capacity deployed at each node. PHS, whose capacity is fixed, is mainly distributed across Western and Southern Europe. Spain is the country with the greatest amount of PHS capacity with 8.1 GW representing 14.3% of Europe-wide PHS installed capacity.

Under the cost-optimal configuration of the future renewable power system, battery storage is dominantly installed in Western, Southern, and Southeastern Europe, surrounding the Mediterranean Sea. While it is marginally installed in the northern parts of Europe, where the UK and Nordic countries have only 2.15% of the 161.1 GW installed across Europe. Italy is the country with the highest battery storage capacity, with 49.6 GW representing 30.76% of all battery storage. Interestingly, Italy is also the country with the highest capacity of installed solar generation, as seen in Figure 4.12, highlighting the diurnal patterns of solar energy and the need for short-term storage such as batteries.

Figure 4.21 Location of storage technologies, Network 2050
Total installed PHS: 54.59 GW; largest node: 8.1 GW (Spain)
Total installed battery storage: 161.1 GW; largest node: 49.6 GW (Italy)
Total installed hydrogen storage: 158.6 GW; largest node: 47.1 GW (United Kingdom)

A similar tendency can be observed for hydrogen storage, of which 29.7% of its capacity is installed in the United Kingdom, the country with the highest onshore wind generation and almost exclusively powered by it. A trend for hydrogen storage capacity can be observed in countries with a high share of onshore wind, such as Denmark, France, Poland, and Finland. Within the modeled system, the long-term and short-term needs for storage technologies are ultimately driven by the renewable generation availability at different locations, and also by the energy storage and power capacity costs inputted as parameters.

Overall, Italy, France, and the United Kingdom are the countries with the greatest power capacity of storage throughout the three different modeled networks; 2030, 2040, and 2050. In 2030, Italy has a cumulative storage power capacity of 55 GW, and increases to almost 59 GW by 2050. The share of battery storage ranges between 85.3% in 2030 and 84.5% in 2050 emphasizing the need for short-term energy storage due to the amount of solar energy. PHS is the second dominant storage technology in Italy, with a share of 14.2% in 2030 and 13.3% by 2050. On the other hand, France's storage capacity ranges from 39.7 GW of power capacity in 2030 to 46 GW in 2050. In 2030, 56.2% of France's storage capacity is made up of hydrogen storage, 30.5% of batteries, and the rest of PHS. While in 2050, its storage technology mix changes to 60.3% hydrogen, 28.2% batteries, and 11.5% PHS. A 91.63% share of the 33 GW of storage power capacity installed in the United Kingdom in 2030 is hydrogen storage, followed by an 8.3% share for PHS. By 2050, the UK's storage capacity increases to 49.9 GW of which 94.3% is hydrogen and 5.7 PHS.

Figure 4.22, Figure 4.23, and Figure 4.24 summarize visually the installed storage power capacities and the storage technology mix for every country for the network 2030, network 2040, and network 2050, respectively. The results can also be found in Table 8.4, Table 8.5, and Table 8.6 in the Appendix.

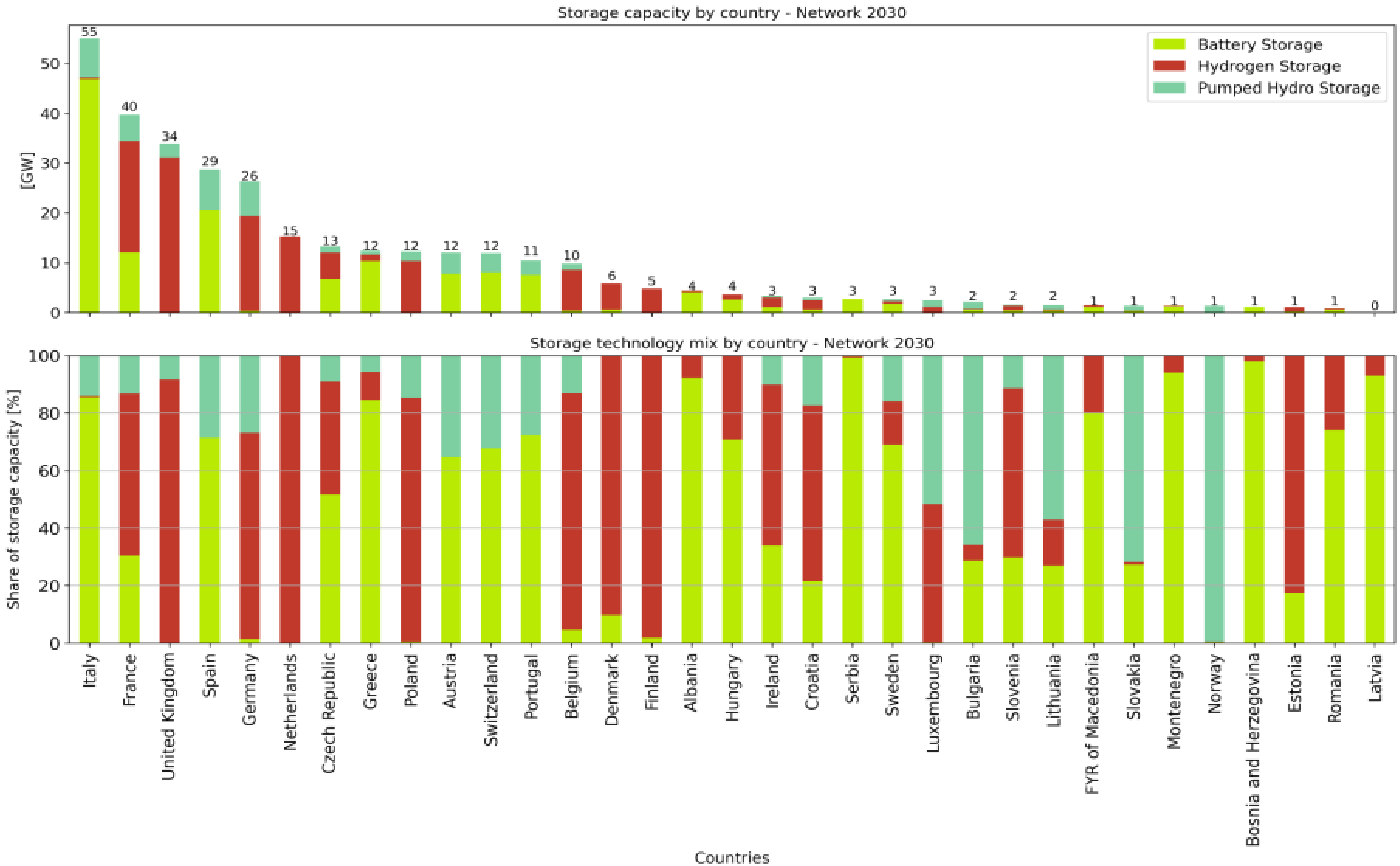

Figure 4.22 Optimal installed power capacities of storage technologies and storage technology mix for each country, Network 2030. Corresponding results are presented in Table 8.4in the Appendix.

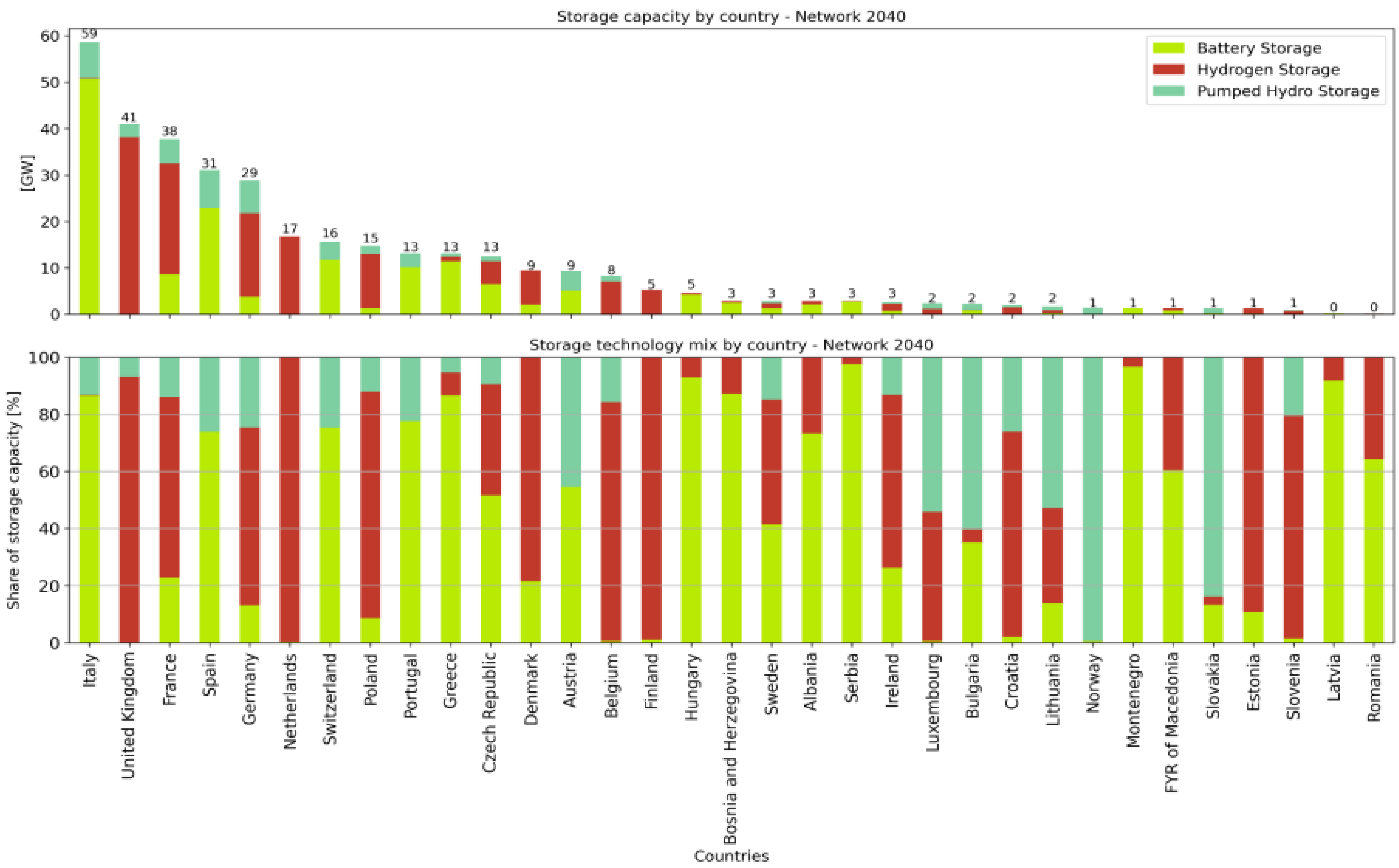

Figure 4.23 Optimal installed power capacities of storage technologies and storage technology mix for each country, Network 2040. Corresponding results are presented in Table 8.5in the Appendix.

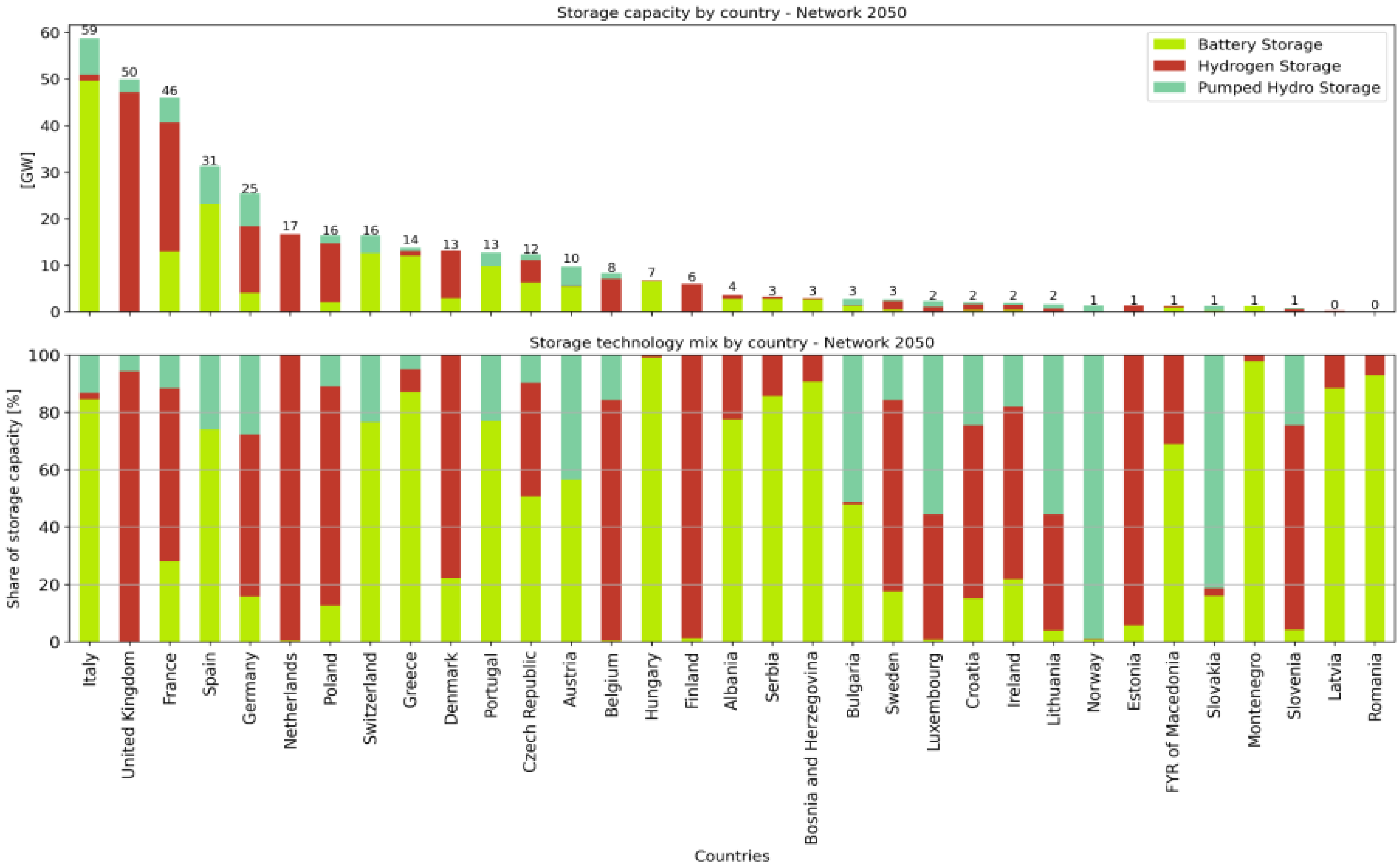

Figure 4.24 Optimal installed power capacities of storage technologies and storage technology mix for each country, Network 2050. Corresponding results are presented in Table 8.6 in the Appendix.

4.3.5 Transmission Expansion

The modeled development trajectory scenarios are not only differentiated by their electricity demand profiles and forecasted renewable generator costs, but also by constraints imposed on the volume expansion of the European transmission network. The volume constraint limits the total volume of line expansion by a certain factor of the currently modeled line capacities weighted by the individual line lengths. The volume factor does not apply to each transmission line individually but rather applies to the total expansion of the network. In that sense, the most welfare-increasing expansions are prioritized. As described in section 3.4.3, the 2030 network was limited by a factor of 1.55 of existing capacity in the model, network 2040 was limited by a factor of 1.75, and network 2050 was limited by a factor of 2. No new HVAC lines and HVDC links are created within the optimization, however, projects included in the TYNDP 2018 are considered expandable, even though their original capacity is set at 0.

An overview of the HVAC lines and HVDC links considered in the clustered 37-node European power system, as well as their optimal capacities throughout the development trajectory networks, is shown in Table 4.6 and Table 4.7, respectively. Furthermore are visually represented in Figure 4.26, Figure 4.27, and Figure 4.28 in section 4.3.7 Results overview.

For HVAC lines, the transmission lines from Germany to Denmark is the one with the greatest increase in capacity. Having 4.5 GW of transmission capacity in the existing modeled transmission network, increasing its capacity to 30.2 GW by 2030 and ultimately 33.5 GW by 2050. Poland, with high onshore wind generation capacity, expands its HVAC lines to the Czech Republic and Slovakia from its current 4.5 GW and 3.4 GW capacities to 18.1 GW and 19.8 GW by 2050.

As for HVDC links, two major expansions are noted. First, an HVDC transmission line currently under construction and no current transmission capacity from the UK to Belgium is expanded to 14.2 GW in 2030 and increases its capacity further to 37.4 GW by 2050. Another major expansion is another HVDC link under construction connecting Germany to Belgium. This HVDC link has a cost-optimal capacity of 8.3 GW by 2030 and increases to 27.9 GW by 2050. These two major expansions ultimately create a bridge between the UK and Germany, being the latter the country with the greatest number of interconnections with other countries. Furthermore, the UK and Germany are the third and fourth countries with the highest generation capacity and have complimentary onshore wind and solar generation portfolios. Thus, the rapid expansion of these lines prioritized in all networks by the optimization suggests towards the cost-effectiveness of connecting the UK to mainland Europe. Interestingly, Italy, one of the countries with the highest generation capacity, does not see a major expansion of its transmission capacity.

Table 4.6 HVAC Line expansion overview [GW]
Country 1 is the country of origin of the transmission line, Country 2 is the end of the transmission line

Country 1	Country 2	Existing	2030	2040	2050
Albania	FYR of Macedonia	0.00	0.21	1.13	1.98
	Greece	1.70	1.70	1.70	1.70
	Montenegro	2.27	2.27	3.89	5.34
	Serbia	2.27	2.27	2.27	2.27
Austria	Czech Republic	4.53	5.20	5.35	5.30

Country 1	Country 2	Existing	2030	2040	2050
	Germany	16.43	16.43	16.43	16.43
	Hungary	4.53	4.53	4.72	5.44
	Italy	0.57	1.01	1.17	1.08
	Slovenia	0.57	4.50	5.75	6.02
	Switzerland	6.79	6.79	6.79	6.79
Belgium	France	9.63	9.63	9.63	9.63
	Luxembourg	1.14	2.57	3.06	3.16
	Netherlands	6.79	6.79	6.79	6.79
Bosnia and Herzegovina	Croatia	5.67	5.67	5.67	5.67
	Montenegro	2.84	2.84	2.84	4.09
	Serbia	2.27	2.27	2.27	2.27
Bulgaria	FYR of Macedonia	1.70	1.70	1.70	1.70
	Greece	1.70	1.70	1.70	1.70
	Romania	6.79	6.79	6.79	6.79
	Serbia	1.70	1.70	1.70	1.70
Croatia	Hungary	6.79	6.79	6.79	6.79
	Serbia	1.70	1.70	1.70	1.70
	Slovenia	6.23	6.23	6.23	6.23
Czech Republic	Germany	6.79	7.23	8.51	9.91
	Poland	4.53	12.00	15.44	18.07
	Slovakia	6.23	6.23	6.23	6.23
Denmark	Sweden	3.40	3.40	3.40	3.40
Estonia	Latvia	2.12	3.50	4.12	4.39
FYR of Macedonia	Serbia	3.40	3.40	3.40	3.40
Finland	Sweden	3.40	3.40	3.40	3.40
France	Italy	5.66	5.66	6.03	7.07
Germany	Denmark	4.53	30.15	33.07	33.51
	France	9.63	9.63	9.63	9.63
	Luxembourg	3.98	3.98	3.98	3.98
	Netherlands	13.58	13.59	13.58	13.58
	Poland	6.79	6.79	6.79	6.79
Greece	FYR of Macedonia	3.40	3.40	3.40	3.40
Hungary	Romania	3.40	3.48	5.15	5.94
	Serbia	1.70	2.30	3.05	3.92
	Slovakia	3.40	7.48	11.62	15.12
Italy	Slovenia	2.27	4.72	5.66	5.39
Lithuania	Latvia	4.23	4.23	4.23	4.23
Montenegro	Serbia	2.84	2.84	2.84	2.84
Norway	Sweden	7.36	9.01	9.74	10.80
Poland	Slovakia	3.40	11.05	15.84	19.84
Romania	Serbia	5.09	5.09	5.09	5.09
Spain	France	4.53	4.53	4.53	4.53
	Portugal	15.29	15.29	15.29	15.29

Country 1	Country 2	Existing	2030	2040	2050
Switzerland	France	10.21	13.93	15.97	18.60
	Germany	27.17	27.17	27.17	27.17
	Italy	8.50	8.50	8.50	8.50
United Kingdom	Ireland	1.14	2.21	3.91	5.59

Table 4.7 HVDC Link expansion overview [GW]

Country 1	Country 2	existing	2030	2040	2050
Denmark	Denmark	0.60	0.93	0.68	0.60
	Germany	0.60	4.60	4.67	4.69
Finland	Estonia	1.25	2.59	2.91	3.12
France	Spain	2.00	8.32	11.80	14.82
	United Kingdom	0.00	0.00	0.00	0.00
Germany	Belgium	0.00	8.29	17.14	27.96
	Norway	0.00	0.00	0.00	0.00
Italy	Greece	0.50	0.50	0.50	0.50
	Italy	1.30	1.30	1.30	1.35
	Montenegro	0.00	0.16	0.37	0.36
	Switzerland	0.00	3.10	4.97	6.13
Lithuania	Sweden	0.70	0.70	0.70	0.70
Netherlands	Denmark	0.00	4.73	4.08	3.42
	Norway	0.70	0.70	0.70	0.70
Norway	Denmark	0.94	7.42	6.88	6.62
	United Kingdom	0.00	0.16	1.06	3.05
Poland	Lithuania	2.00	2.90	3.16	3.22
	Sweden	0.60	0.87	2.06	3.31
Spain	France	0.00	0.00	0.00	0.00
	Spain	0.40	0.40	0.46	0.52
Sweden	Denmark	0.55	3.28	3.64	4.01
	Finland	1.30	2.65	3.40	3.94
	Germany	0.00	0.00	0.00	0.01
United Kingdom	Belgium	0.00	14.19	25.29	37.36
	Denmark	0.00	0.00	0.00	0.00
	France	2.00	7.15	12.37	17.07
	Germany	0.00	0.00	0.00	0.00
	Netherlands	1.00	3.87	4.58	5.22
	United Kingdom	2.75	2.76	4.15	8.94

4.3.6 Total System costs

Figure 4.25 depicts the composition of the total annualized system costs and the average system cost per unit of generated energy for each of the multi-renewable development trajectory networks. Note first that the total annualized system costs follow a similar increasing trend to the installation of generation and storage technologies presented in previous sections.

From a European-aggregated perspective, the overall technology composition of the system remains relatively stable across the different horizons, where solar and onshore wind represent between 93%-95% of installed generating capacities. The increasing installed capacities of generating and storage technologies over the different horizons ultimately translate to increased system costs and are mainly driven by the increased demand set as a parameter for each reference year and described in section 4.3.2. Nonetheless, the decreasing costs of technologies and the different network expansion constraints set for the different horizons counteract to a certain degree the annualized system costs of the power system.

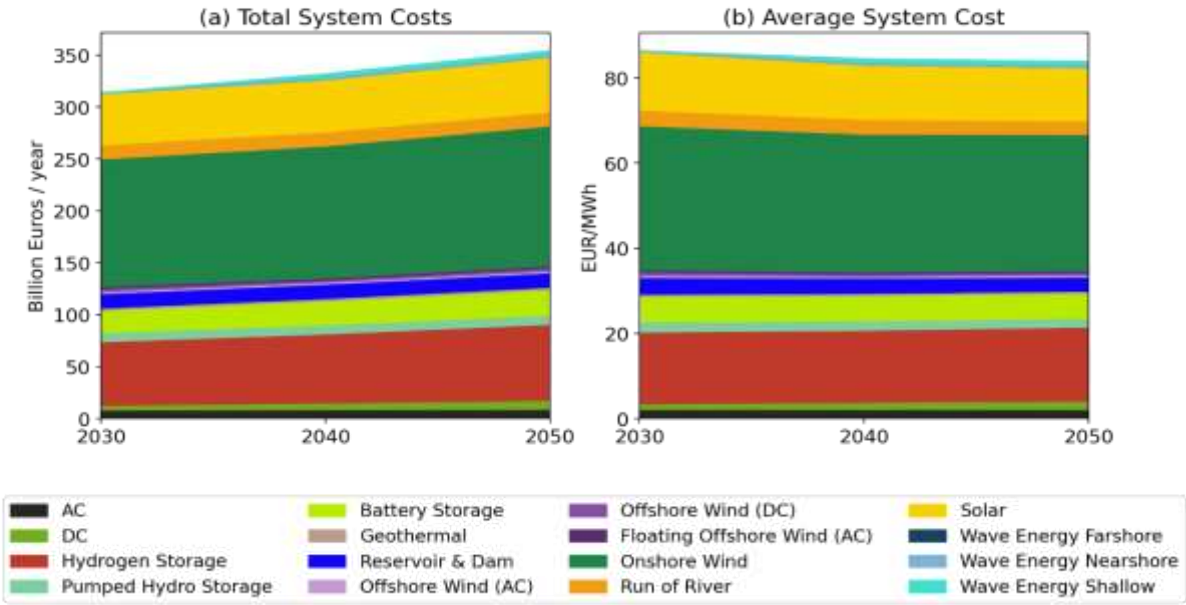

Figure 4.25 Annualized total system costs (a) and average system costs per unit of generated energy in €/MWh for the development trajectory networks
Note: The costs include existing infrastructure that was not expanded during the optimization, such as existing transmission lines, PHS, run of the river, etc.

This can be better observed in plot (b) of Figure 4.25, where the average system costs per unit of energy generated show a decreasing trend, declining from an average of 86.32 €/MWh in 2030 to 83.78 €/MWh in 2050. Cost reductions were considered for all generating technologies modeled using cost estimates from the JRC and the Danish Energy Agency, as well as the learning curve approach for WECs. These cost reductions not only have an impact on the ultimate configuration of the network but also represent a decrease per MWh cost of energy generated. Furthermore, the transmission expansion constraints for the 2030, 2040, and 2050 networks also plays a role in the decreasing trend of the average cost. Schlachtberger et al. (2017) and Hörsch et al (2017) have found that total system costs decrease nonlinearly according to allowed transmission volume expansion. The closer the volume expansion constraint is to the existing/original network the higher the costs, but as the expansion constraint gets closer to the optimal expansion, the costs rapidly decrease and ultimately stabilize at a point where costs are insensitive to transmission expansion. This is further discussed in the transmission expansion sensitivity analysis in the discussion section (Section 5.2).

4.3.7 Results overview

In this section, a visual overview of the results of the different networks are depicted in Figure 4.26, Figure 4.27, and Figure 4.28 for Network 2030, Network 2040, and Network 2050, respectively. The node for each country showcases the technology mix of generating and storage technologies based on the power capacities, while the size of the bus represents the magnitude of capacity installed in that region. Furthermore, the figures display the existing and expanded transmission HVDC and HVAC transmission lines. The existing transmission infrastructure is shown in purple, while the capacity expansion of certain lines is shown in red.

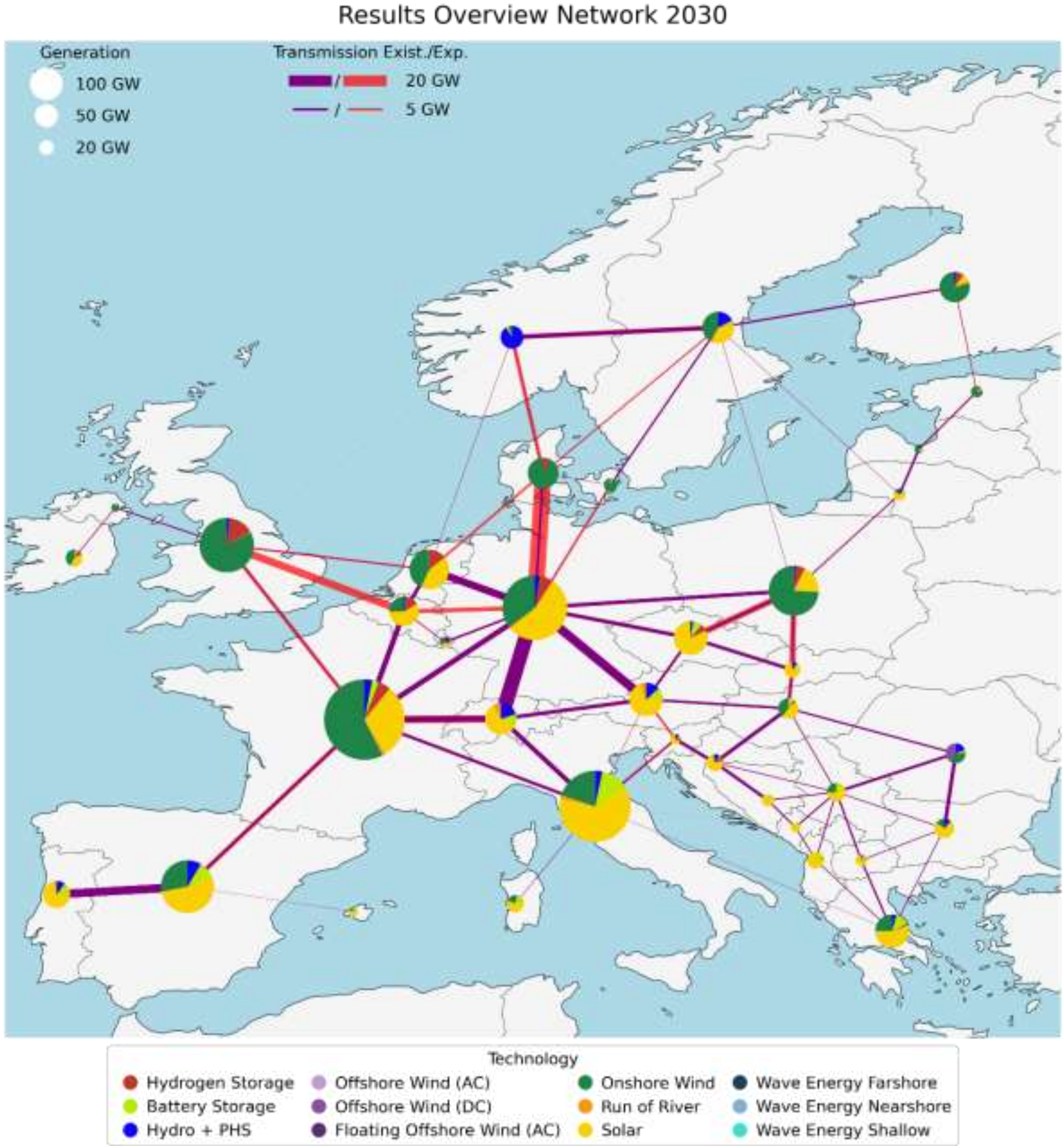

Figure 4.26 Results overview for network 2030

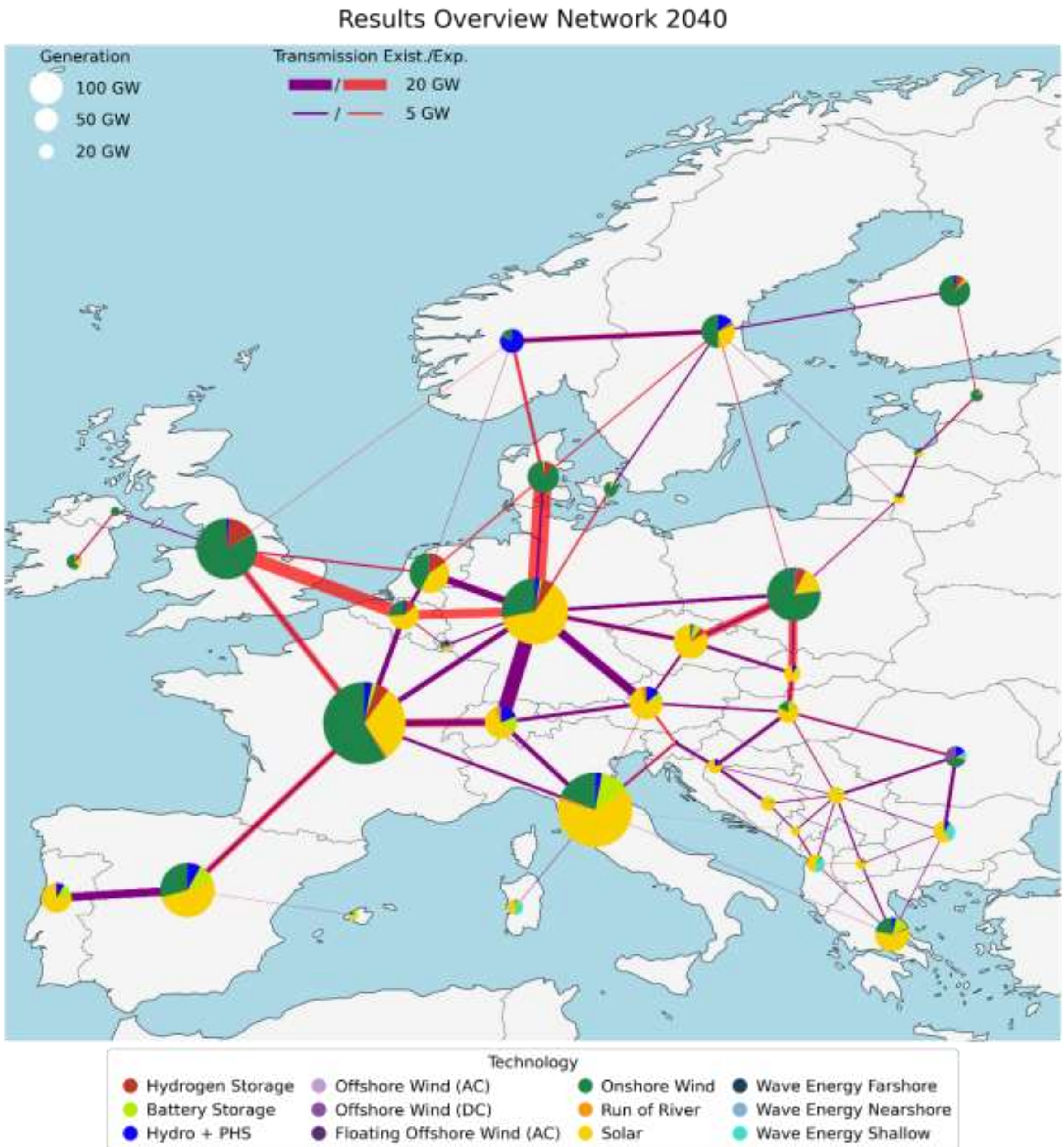

Figure 4.27 Results Overview for network 2040

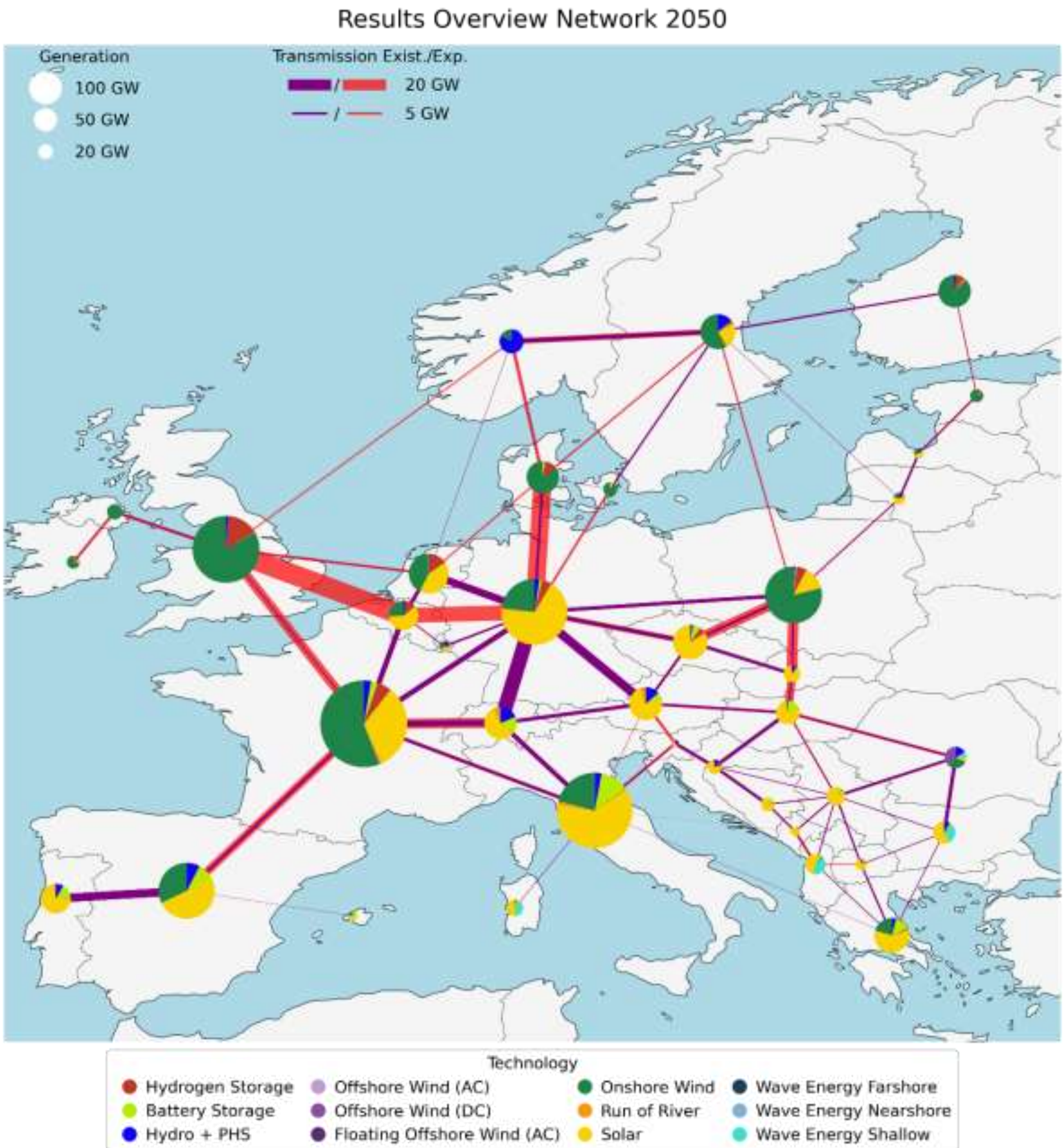

Figure 4.28 Results Overview for network 2050

5. Discussion & Limitations

In this section a discussion of the results primarily focused on Network 2050 is provided. First the resource assessment results estimated by the model are discussed and compared against literature. Secondly, given the resulting cost-optimal configuration of a renewable European power system by 2050, the global system dynamics and the power system behavior are discussed. This is followed by a similar discussion at a regional level, by comparing 3 countries with different resulting diversity in their power generation portfolios and their wave energy penetration. Furthermore, a sensitivity analysis on the impact of allowed transmission expansion for Network 2050 is provided. Lastly, the limitations of the model and the integration of the wave energy resource are presented.

The objective of this research is to understand the general system dynamics of a future multi-renewable European power system and the potential role that wave energy may play within these future power systems. The novel expansion of the renewable energy capabilities of the PyPSA-Eur model allowed for the assessment of the wave energy resource across Europe's coastlines for the respective year. Allowing to estimate the renewable wave energy capacity potentials restricted by depth, packing rate, and land availability, derive renewable wave generation availability time series of the WEC devices according to their power matrices and the characterized sea-states, and ultimately consider the wave energy resource and technologies in a cost-based power flow optimization of the European transmission grid.

First, the resource assessment performed by the model deserves special mention. Given the eligibility criteria determined for each device, the resource assessment resulted in an aggregated geographic potential of 20.3 TW, 14.7 TW, and 2.4 TW for the Farshore, Nearshore, and Shallow device, respectively. These showcase the available technical potential without considering cost effects.

By combining the maximum installable capacity with the yearly average capacity factors of each grid cell (2018 weather data), an approximation of the maximum power generation potential is estimated and resulted in an aggregated 23,840 TWh for the Farshore device, 9,642 TWh for the Nearshore device, and 2,533 TWh.

Although the global wave resource is still under debate, it has been estimated in the range of 1-10 TW of incoming resource per year. This sensitivity highly depends on the definition of wave power flux and the underlying datasets used, recent studies provide us with an estimate of global wave power incoming resource ranging between 29,500 TWh/yr and 32,000 TWh/yr (Guo & Ringwood, 2021; IRENA, 2020b; Mørk et al., 2010; Reguero et al., 2015). Furthermore, Pontes (1998), estimated that the total annual resource along the Atlantic coasts of Europe amounts to 290 GW. All of these consider a resource-only approach and do not consider a joint distribution and/or a specific type of device, as was done in the present research but rather the amount of TWh that reaches the coastlines per year, not what is extractable.

Moreover, the 20 MW/km^2 packing density inputted as a parameter for all devices is on the high end of the feasibility range considered by Lavidas and Blok (2021), without accounting for array optimization.

In addition, the aggregated maximum power generation potential needs to be taken with extreme caution, as this aggregation by grid cell ignores the potential power extraction from one grid cell to another and assumes the sea-state characteristics remain unchanged. Thus, this estimation of power generation potential derived from the maximum installable capacity and average yearly capacity factor per grid cell serves better to identify locations with both extensive land availability and highly productive sites, as it is employed by the model, rather than as an aggregated technical resource estimation. Highlighting that any assessment of the extractable wave power requires a detailed study of local conditions with custom studies to corroborate. Nonetheless, it is considered that the present addition of the model is appropriate for wave energy assessments at early stages of development.

Secondly, a set of 100% multi-renewable power system scenarios were modelled at the horizons of 2030, 2040, and 2050 considering cost-reduction potentials of wave energy and other generating technologies, as well as expected demand increase, and transmission capacity constraints. In the previous section, the results of these scenarios were presented with each network component (generators, storage, and transmission capacity) across the different scenarios presented independently. As a general overview, the three-resulting cost-optimal configurations of the European network were very similar.

Solar and onshore wind dominated the deployed generating technologies installed extensively across Europe representing between 48-47% and 45-47% respectively of the overall generation mix across the different horizons. Total installed generating capacity grew from 2.37 TW in network 2030 to 2.72 TW in network 2050, following the increased electricity demand inputted exogenously. This was followed by existing hydroelectricity generation which was not optimized or extended with an aggregated fixed capacity of 99 GW. Wave energy shallow and offshore wind (DC) where the two offshore technologies most widely deployed. WEC Shallow cost reductions seem to have provided a cost-competitive advantage in some locations as its capacity grew from only 12 MW in 2030 up to 30.9 GW in 2050 and was installed mainly in the Black and Mediterranean Seas. Offshore wind (DC) was essentially only installed in Romania in the Black Sea with a capacity of around 11.8GW and remained relatively constant throughout the horizons. Other offshore energy converters (wave energy nearshore, wave energy farshore, offshore wind (AC), and floating offshore wind) were minimally installed with total installed capacities in the order of magnitude of MW with a combined share of less than 0.04% of the total deployed capacity. Although these results almost satisfy the 40 GW specific target of ocean energy in the EU Strategy on Offshore Renewable Energy, they fall extremely short of the overall target of 300 GW of offshore energy by 2050 with only 42.8 GW of aggregated offshore capacity by 2050.

Meanwhile, the dominance of solar and onshore wind and their respective generation patterns seem to heavily impact the location and hourly dispatch of backup electricity storage. Storage power capacity grew in line with the increased demand from 328 GW in 2030 to 374 GW in 2050. Battery storage share remained around 43% while for hydrogen it ranged between 40% and 42%. PHS power and energy capacity remained fixed similar to generating hydro. Regarding transmission lines, cross-border connections between the UK, Germany, and Denmark were prioritized through all horizons and suggest they provide the most welfare for the system.

The rest of the discussion will primarily focus on how these network components behave and interact with each other firstly at a European level, and secondly, at a regional level focusing on locations with multi-renewable energy portfolios. The Network 2050 scenario was selected for this discussion since it has a greater diversity of generating technologies. Furthermore, a discussion on the sensitivities of the model is provided, mainly focused on the cost-optimal configuration sensitivity to transmission expansion constraints. Lastly, the limitations of the research and the model are discussed.

5.1 Power system behavior

In brief, the model minimizes total annualized system costs considering the variable and fixed costs of generation, storage, and transmission given a set of technical and physical constraints expressed mathematically assuming perfect competition and foresight. It is a partial equilibrium model of the electricity sector that can optimize both short-term operation and long-term investment of the European power system as a linear problem, employing linear power flow equations. Variable renewable generators (solar PV, onshore wind, offshore wind, and wave energy), storage power and energy capacities (batteries and hydrogen storage), and transmission capacities (HVDC and HVAC lines) are all optimized. Meanwhile, the electricity demand, conventional renewable generators (hydroelectric, run-of-the-river, and geothermal), and storage capacity of pumped hydro storage are either modeled or exogenous to the model and are not optimized during the simulation runs. The model was executed under an hourly resolution and a 37 clustered node network, essentially one node per country, and employing 2018 weather data from the ERA5.

In addition, the hourly dispatch of generators and storage is also optimized to meet electricity demand at every snapshot of the year. Figure 5.1 depicts an illustrative sample of Network 2050 for December of how the system behaves at an aggregated European level. The figure showcases aggregated dispatched generation, curtailed generation, storage discharge, and storage charge and is plotted against the respective electricity demand. It can be observed that at every hour, there is sufficient available energy to satisfy this demand. This is mainly satisfied by dispatched generation from renewable technologies (blue), but the need for storage (dark orange) can be seen during some periods. Additionally, note that in some periods dispatched generation is greater than the load itself, usually when there is also curtailed electricity. This additional dispatch corresponds to the action of storing energy in one of the available storage technologies, shown in this figure as negative values in light orange.

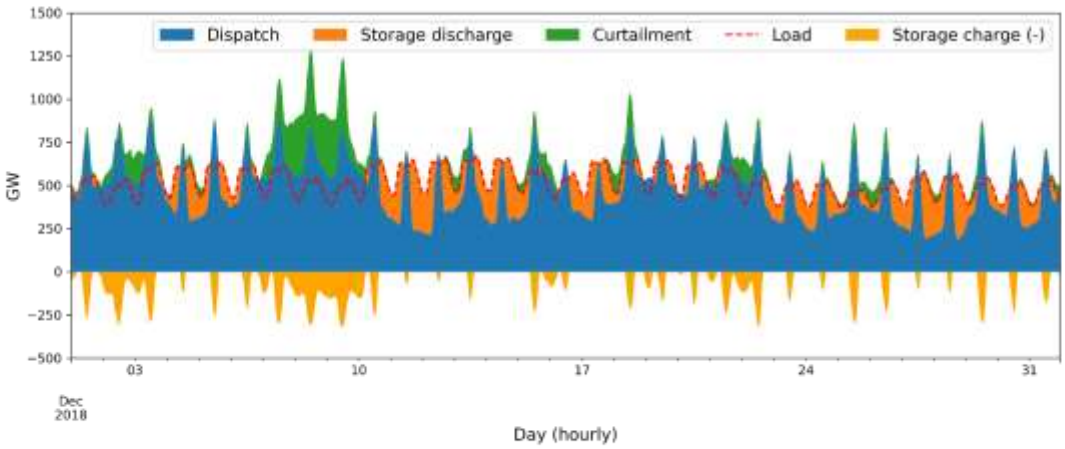

Figure 5.1 European-aggregated system behavior overview, December, Network 2050

Available generation (dispatch plus curtailed generation) is characterized by diurnal patterns, with peak available generation during the day. This is attributed to the dominance of solar energy, which represents approximately 47% of the installed capacity for the 2050 network. Nonetheless, not all available generation is dispatched into the power system, and curtailment of available electricity is present. Some reasons explain why curtailed energy is not being utilized. The main one is that it is not cost-effective to do so, given that it is a cost-minimizing optimization, and the problem formulation also minimizes operational costs. However, the figure does not provide information on where the available generation is located and if there exists available storage capacity to store it, which may explain why it is not being utilized. Furthermore, limits on transmission capacity also may limit the ability to transport and utilize available electricity from renewable generators where it may be needed.

Similarly, Figure 5.2 summarizes how the different network components behave across the whole simulated year. The heatmaps have the hour of the day on the x-axis and the day of the year on the y-axis. They visually summarize how the system behaves across the different seasons and hours of the day. Firstly, the Load factor (a), calculated as the division between the sum of electricity demand for all countries divided by aggregated peak electricity demand, showcases both daily and seasonal variability. Electricity demand is higher around the winter season. And on a daily basis, high demand is observed from 6:00 am until around 7:00-8:00 pm. Dispatched generation (b), calculated as the division between the sum of generated power by the sum of installed nominal power capacities, showcases a diurnal pattern, with midday displaying the highest amount of dispatched electricity. These also correspond to the peaks observed in Figure 5.1, attributed to the amount of solar PV installed. Curtailed electricity (c), normalized by its maximum value, displays a similar diurnal pattern as dispatched generation, although the spring and autumn seasons seem to have higher peaks of curtailed electricity, corresponding to lower electricity demand. Storage charging (e) and storage discharging (f) display complementary patterns, where energy is stored during the day when there is available generation from renewable sources and is discharged during the night to satisfy the lack of power generation. Nonetheless, the state of charge (d) of the aggregated storage, calculated as the sum of stored energy by the aggregated nominal energy capacity, varies across the year, with summer and winter as the seasons with the greatest amount of stored energy and discharged around the spring and autumn seasons.

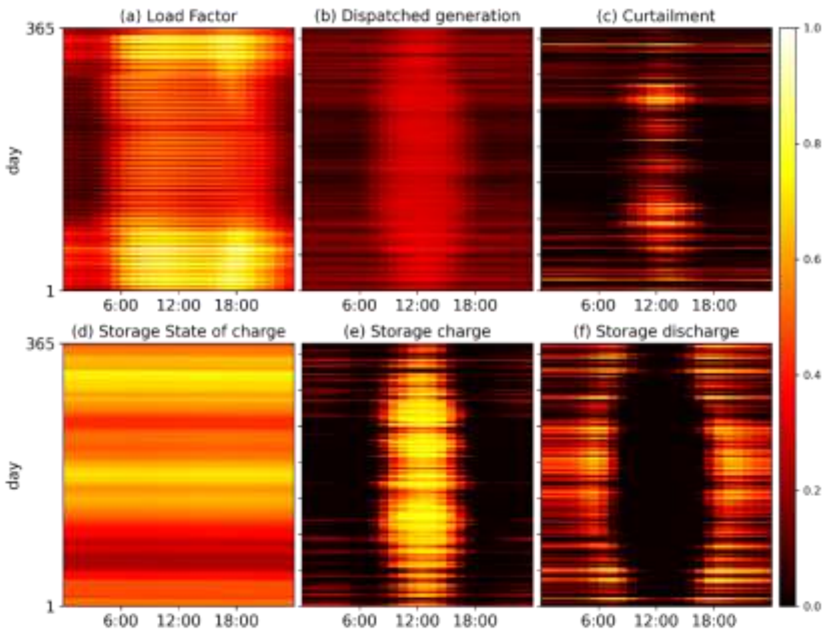

Figure 5.2 Normalized European-aggregated system dynamics for the whole year, Network 2050
(a) Load factor is calculated as the aggregated load every hour divided by the peak aggregated load (703 GWh).
(b) Dispatched generation is normalized by dividing dispatched generation by total installed generation capacity (2,619 GW)
(c) Curtailment is normalized by the maximum aggregated curtailment (572 GWh).
(d) Storage state of charge is calculated as the aggregated stored energy divided by the nominal energy capacity of all storage techs. (242 TWh)
(e) Storage charge is calculated by aggregated active power consumed for charging divided by the sum of all storage power capacities
(f) Storage discharge is calculated by aggregated active power dispatched divided by the sum of all storage power capacities

Figure 5.2 (b) plotted dispatched generation by aggregating all generators installed in the system. On the other hand, Figure 5.3 plots similar information but differentiating by each installed renewable generating technology. It was calculated as the division between the sum of generated power, for every generating technology, in all countries by the sum of their installed nominal power capacities. In essence, this can be interpreted as the hourly European average capacity factor for each technology subject to the locations where it was installed. Note that the plot also provides information and the installed nominal capacity of each technology, enabling to identify their respective relevance it has for the power system as a whole. It can be seen by comparing both figures, that the aggregated dispatched generation (Figure 5.2 (b)) is effectively a combination of the solar and onshore wind profiles, given that together they represent 93.5% of the installed generation capacity and were installed in essentially every country. Wave Energy Shallow (h) and Offshore wind DC (c) are the two offshore technologies with the greatest amount of capacity installed. Wave energy shallow was installed mainly installed in the Black Sea on the coasts of Romania and Bulgaria (40% of installed total WEC shallow capacity), the Ionian Sea on the coast of Albania (47%), and around the coasts of Sardinia, Italy (22.4 %). The wave energy resource on these coasts seems to be higher during winter months, with an aggregated capacity factor of between 30% and 40%, and lower than 20% during the summer months. Offshore wind DC was essentially exclusively (99.9%) deployed in the Black Sea on the coasts of Romania, and it presents very high capacity factors of above 80%, subject to weather data from the year 2018. Other technologies in the Figure were not widely installed, thus their capacity factors shown may not be representative.

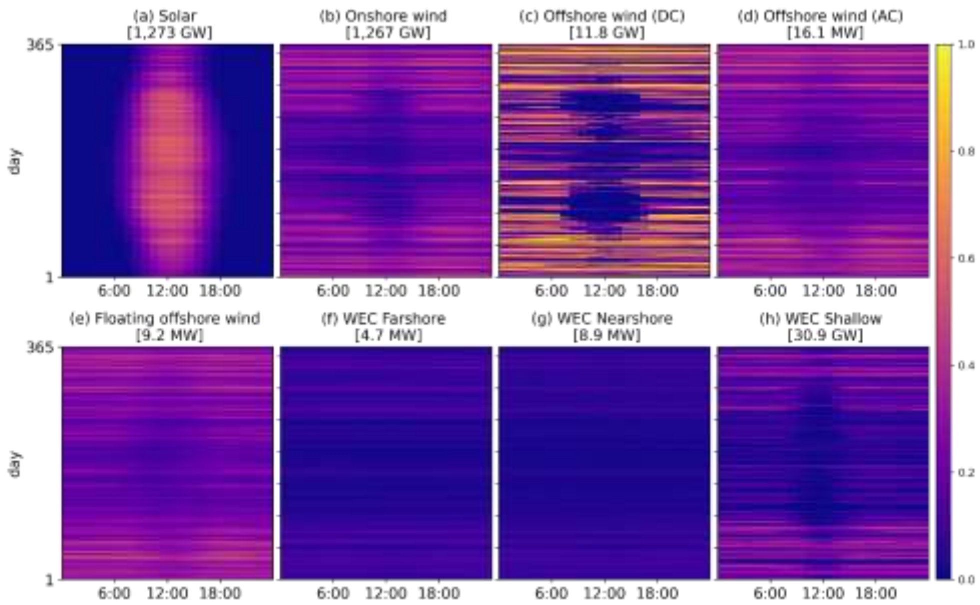

Figure 5.3 European aggregated power dispatch of technologies per installed nominal capacity. Calculated as the division between the sum of generated power, for every generating technology, in all countries by the sum of their installed nominal power capacities.

Meanwhile, Figure 5.4 depicts heatmaps of the Europe-aggregated charging and discharging power of the different storage technologies. Calculated as the division between the sum of charging or discharging power in all countries by the sum of their nominal power capacities. Charge and discharge ultimately depend on the difference between renewable generation and demand every hour. It can be observed that charging and discharging patterns are predominantly characterized by diurnal patterns, where technologies charge during the day and discharge throughout the night, especially observed for battery storage and PHS. This can most likely be attributed to the high penetration of solar energy and power consumption patterns, highlighting the importance of short-term storage. Hydrogen storage displays larger variability across seasons, also observed in Figure 4.20 in the results section. During summer months hydrogen storage showcases a sharper diurnal pattern similar to batteries and PHS, but the pattern changes during winter months where some days are characterized by constant power production through fuel cells to compensate for low renewable generation and others by hydrogen production through electrolysis when renewable generation is available.

Furthermore, the Figure also displays the state of charge of each technology across the year. The short-term nature of batteries is observed, while the long-term nature of hydrogen and PHS is seen through their seasonal variabilities. The aggregated state of charge plotted in Figure 5.2 (d), above, resembles the behavior of PHS and hydrogen, given that their higher energy-to-power ratios allow them to store large amounts of energy.

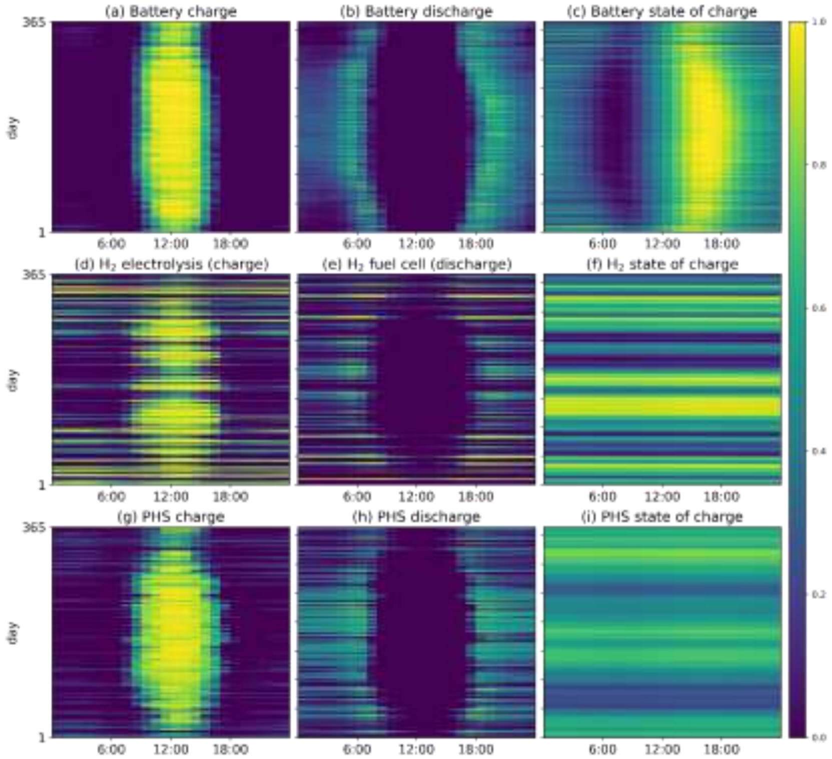

Figure 5.4 Europe aggregated charging and discharging power for storage technologies for Network 2050

In general, from an overall system perspective, the model favors the allocation of solar and onshore wind over other technologies due to them being more cost competitive. In fact, in some cases the model favors binary results, showcasing a fully onshore wind configuration for the UK and Denmark, or fully solar configurations in countries like Bosnia and Herzegovina and Serbia. The dominance of these technologies thus characterizes the behavior of the overall system. In fact, the deployment of the different storage technologies in different locations is correlated and can be explained, to a certain extent, by the deployment of these two mature renewable technologies. Figure 5.5 plots the relationship between generating and storage capacities. Figure 5.5a shows the strong correlation between aggregated generation capacity and aggregated storage capacity (R=0.92, R^2=0.84). Of course, you cannot store electricity if it is not being generated. Nonetheless, the generation capacity of solar and wind seems to distinguish the type of storage technology and the amount of capacity installed in the same location. Country-aggregated solar installed capacity has a moderately strong correlation (R=0.78) with installed battery capacity and suggests that 61.8% of the variation of installed battery capacity can be explained by installed solar capacity. A similar pattern is observed between onshore wind capacity and hydrogen storage with an R-value of 0.88, where onshore wind capacity has strong explanatory power towards the variation of hydrogen storage capacity (R^2=0.77). This highlights the need for short-term storage paired with solar generation and long-term storage with onshore wind generation.

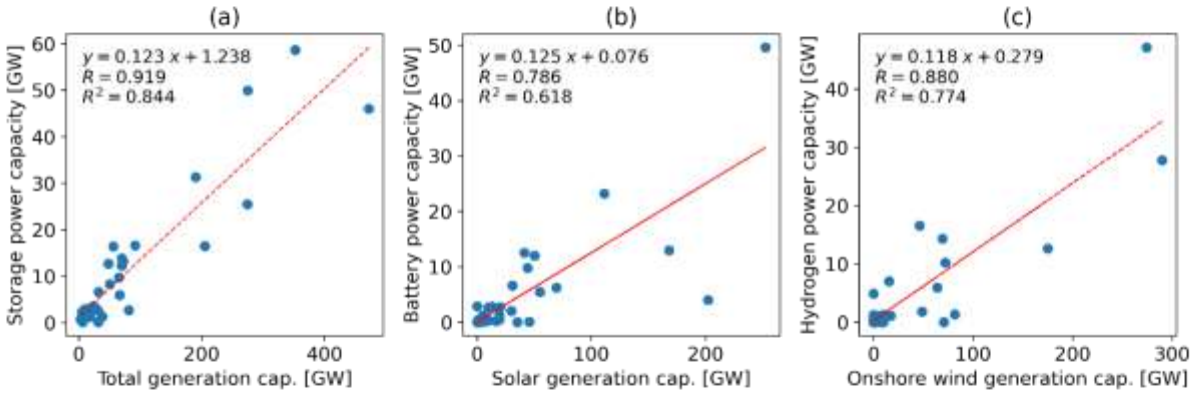

Figure 5.5 Relationship between generation capacity and storage power capacity by country. (a) Aggregated generation capacity vs. aggregated storage power capacity (all technologies). (b) Solar generation capacity vs. Battery storage power capacity. (c) Onshore wind generation vs. Hydrogen storage power capacity.

Although the dominance of solar and wind is an interesting outcome of the future cost-optimal configuration of a high-share multi-renewable European power system, assessing the system from aggregated European perspective does not seem to provide definitive and concrete answers to all the research questions of this thesis. To better understand the interactions and opportunities of multi-renewable power systems that consider the deployment of wave energy and other technologies it is important to scope down and investigate the locations with installed multi-renewable generation portfolios and assess how they may differentiate from regions with non-diversified portfolios.

The Herfindahl-Hirschman index (HHI) is a common measure of market concentration employed in many sectors to describe the concentration or diversification of a portfolio of energy resources from different supplies (de Rosa et al., 2022). The index is calculated as the sum of the squares of each market share of a given portfolio, in this case using the share of total installed capacity by country. It can have a maximum value of 1, occurring when there is only a single share, and has a tendency towards 0 the more diverse a portfolio is. Figure 5.6 plots the HHI calculated for each country in the power system configuration of Network 2050. Countries with fully onshore wind or solar configurations, such as the UK, Denmark, or Serbia have an HHI of 1. Meanwhile, the country with the most diversified energy portfolio is Romania, followed by Latvia and Slovenia, with HHI values of 0.26, 0.34, and 0.35, respectively.

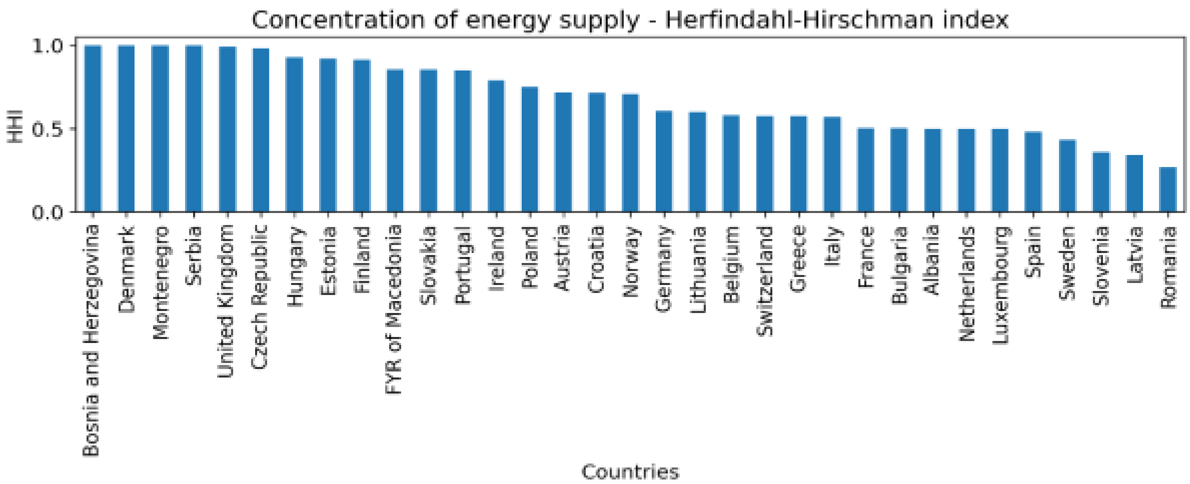

Figure 5.6 Herfindahl-Hirschman index – Concentration of energy supply, Network 2050

Three countries were chosen for the regional assessment based on their HHI, their generation portfolios, their share of wave energy capacity, and similar aggregated generation capacity. Firstly, Romania was selected because it is the country with the smallest HHI (0.27), hence having the most diversified generation portfolio. Interestingly, Romania is also the country with the least amount of storage in 2050 with only 129 MW of storage power capacity. However, no correlation (R-value = -0.03) was found between a multi-renewable energy portfolio (HHI as a variable) and total installed storage power capacity. Secondly, Albania, with an HHI value of 0.50 and a wave energy generation share of 47.1% was selected given the focus of this thesis. Lastly, Hungary with an HHI value of 0.92 and a generation portfolio of solar (96%) and onshore wind (4%) was chosen. Figure 5.7 showcases the generating and storage capacity and technology mix for the selected countries.

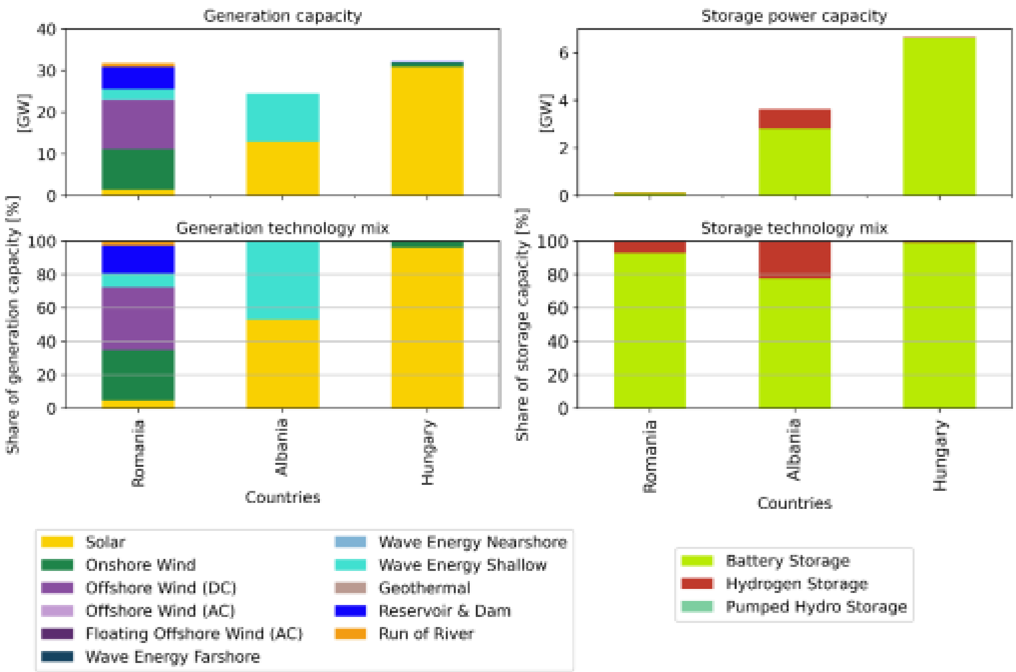

Figure 5.7 Generating and storage technology overview for selected countries, Network 2050.

Figure 5.8 plots an illustrative snapshot, December 21st to December 27th, of the hourly profiles and power balance for each selected country. As has been mentioned before, the dispatch of generating and storage technologies, as well as power flows, is optimized to meet electricity demand at every point in time and every node. At a regional/node level, this also involves power imports and exports, where electricity can be transferred between countries and nodes to meet demand. Ultimately, the dispatch of variable renewable generators is dependent on the installed generation capacity and on the time-series availability of the resource for each specific installed technology (solar irradiation, wind speed, wave height and wave period, etc.). Dispatched generation profiles are shown in Figure 5.9. On the other side, charging and discharging patterns of storage technologies, as well as export and import patterns, are heavily influenced by the dispatch of these renewable generators, as their behavior depends on the mismatch between generation and demand every hour.

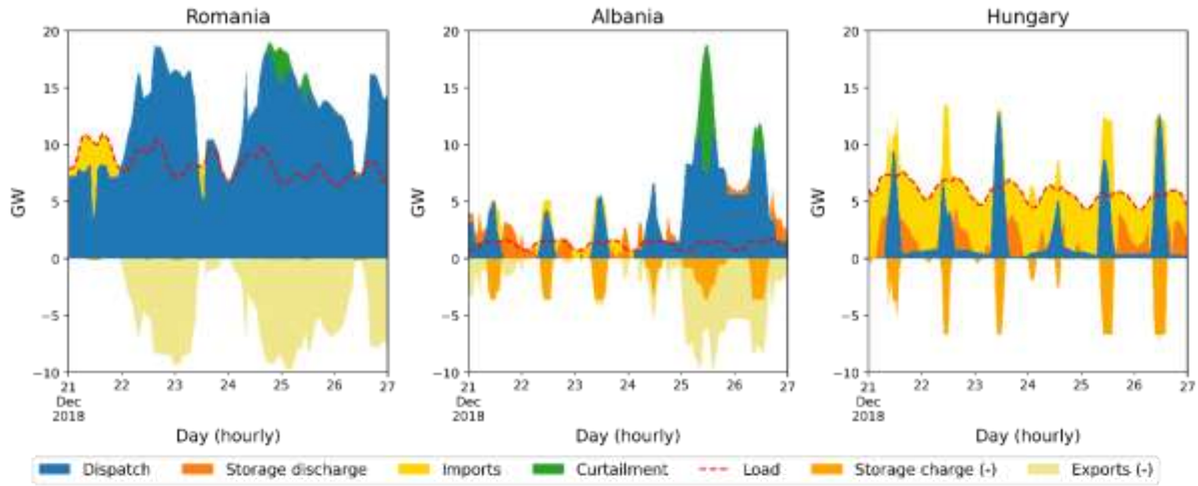

Figure 5.8 System behavior time-series snapshot for selected countries, December 21st to December 27th, Network 2050

Given that these patterns are highly influenced by the hourly generation profile of each country, Figure 5.9 displays the corresponding dispatch by generating technology during the same period. Combining these two figures allows us to discern particular differences between the selected countries. Romania, with the most diversified generation portfolio, displays a much less intermittent generation time series compared to the other two countries, particularly Hungary whose diurnal generation patterns are determined by its mostly exclusive solar generation. Romania's hydro and offshore wind generation seem to satisfy most of its electricity demand, while excess generation from the other technologies is mostly exported. Albania also seems to benefit from a relatively diversified portfolio when both solar and wave energy are available, providing sufficient electricity to meet demand.

Another discernable difference is how excess or insufficient power is balanced in each region. Romania, with only 129 MW of storage power capacity, exports elsewhere most of its excess generation with some of it being curtailed. Albania, when both solar and wave energy are available, mainly exports excess energy that is not used to charge its storage capacity. Hungary, on the other side, seems to be highly dependent on electricity imports, not only to meet its electricity demand but also to store imported electricity to be used during the evening and at night. Wave energy in particular seems to enable a smoother power output profile for both Romania and Albania and is seemingly being dispatched to satisfy energy demand not only locally but elsewhere.

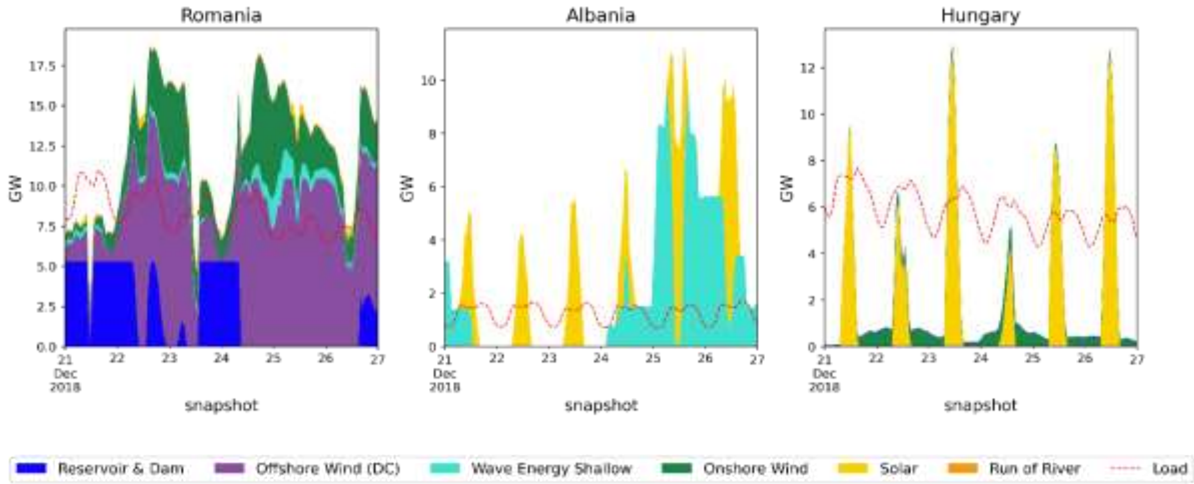

Figure 5.9 Dispatched generation profile of selected countries, December 21st to December 27th, Network 2050

Similar to how it was presented for the overall European power system, Figure 5.10 summarizes with heatmaps the behavior of key parts of the system over the year for each selected country. The electricity demand patterns are similar for the three countries, with greater electricity consumption during the evening on a daily basis and around winter on a seasonal basis. There are, however, differences in the magnitude, with peak loads of 11.42 GWh, 1.89 GWh, and 8.41 GWh for Romania, Albania, and Hungary, respectively. Furthermore, differences in the dispatched generation profiles are visible, dependent on the type of renewable technology, its resource availability, and the load profile. Romania displays a much more stable available and dispatched generation profile than Albania and Hungary, whose profiles are characterized by diurnal patterns due to the strong presence of solar.

An interesting phenomenon is visible in Romania around the summer months and around midday. Note that even though available generation is relatively stable throughout the year, dispatched generation is effectively lower during summer midday hours. During some of the same periods curtailed electricity is at its highest. Furthermore, imports of electricity, shown on the right side of Figure 5.10, also peak around these periods. Thus, this does not mean that generation availability from local renewable sources is lower during these periods, but rather that Romania is importing cheaper electricity from elsewhere, most likely solar, given the time of the day, and curtailing its own, more expensive, electricity generation. This is caused by the absolute electricity trade assumed by the model and the model seeking to minimize operational costs.

Meanwhile, dispatched generation in Albania exhibits a pattern that can be attributed to solar capacity, but the contributions of wave energy, especially around winter can be observed. These patterns are also visible in its exports, shown on the right side of Figure 5.10. Its curtailment resembles solar generation peaks, and interestingly, excess energy seems to be exported throughout the year, particularly wave energy present during the evening and night. Hungary displays patterns determined by its high solar penetration. This results in a high dependence on both imports and batteries. The latter displaying the characteristic short-term storage pattern seen in Figure 5.4.

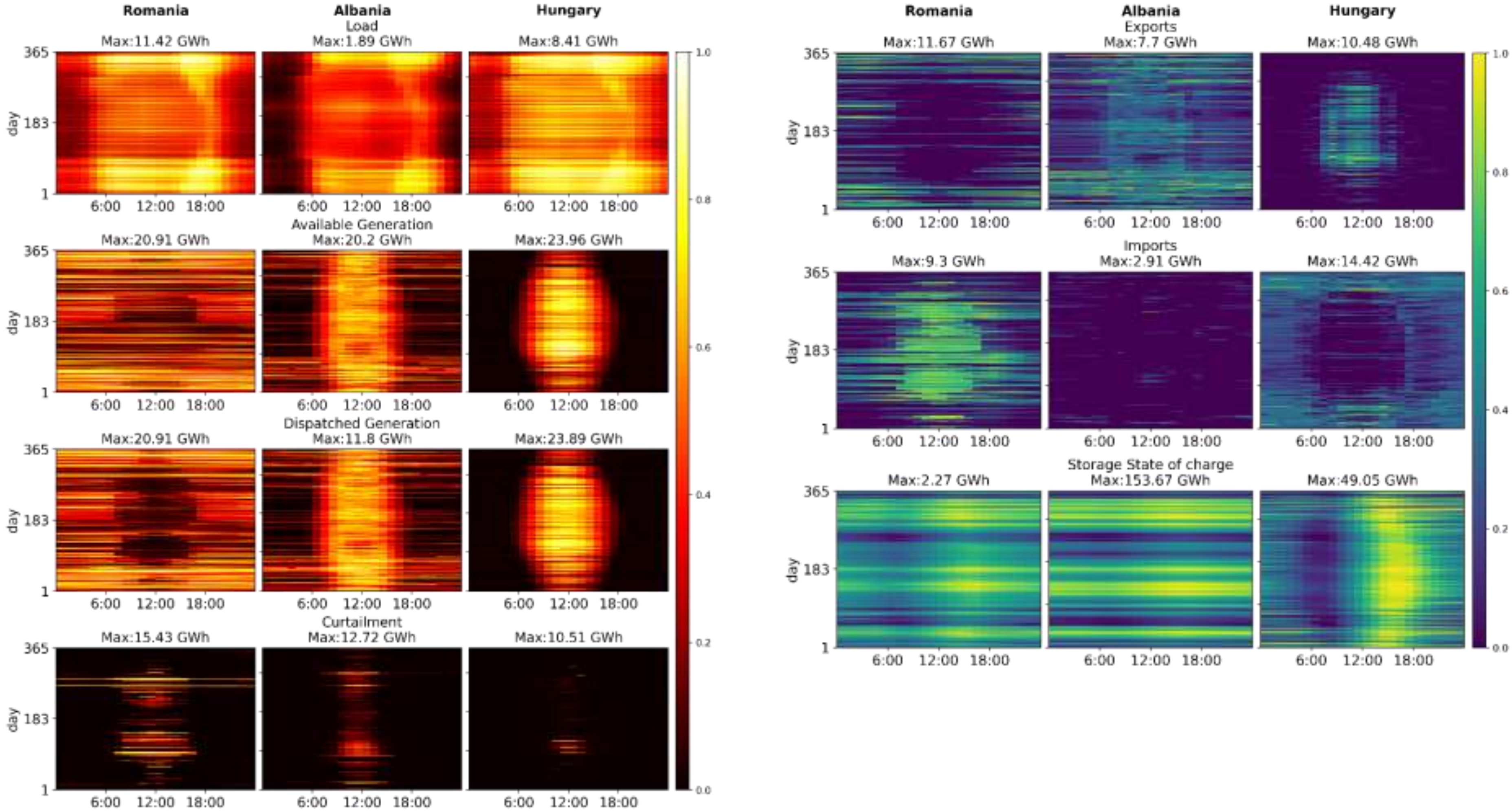

Figure 5.10 Normalized country-aggregated Load, dispatched generation, curtailment, exports, imports, and storage state of charge for selected countries, Network 2050.
*Load is normalized by the peak load of each country
*Available generation and dispatched generation are normalized by the nominal installed capacities of each country
*Curtailment is normalized by the maximum aggregated curtailment
*Imports and exports are normalized by their maximum values for each country
*Storage state of charge is normalized by the nominal energy capacity of all storage techs for each country

Figure 5.11 displays the duration curves of available renewable generation per unit of nominal capacity for the selected countries. The figure strongly highlights the benefits of a multi-renewable energy portfolio. A duration curve serves as a graphical representation of available generation over the year, ordered in decreasing order of magnitude rather than chronologically. It is helpful to identify the stability and reliability of the power supply over a certain period. Hungary, with a solar dominant portfolio, has the ability to generate renewable electricity during approximately only 4000 hours or 45% of the year. Essentially only when the sun is shining. Meanwhile, Albania, with approximately equal shares of solar and wave energy, displays lower peak power production relative to its installed capacity than Hungary, but a much more stable power supply, being able to produce at least a minimum amount of electricity during 6790 hours of the year (77%). Further highlighting some of the benefits of the complimentary nature of wave energy paired with solar. Lastly, Romania, with the most diverse energy portfolio, displays both high peak available power generation relative to its installed capacity, and available renewable generation throughout the year. With an available generation of at least 10% of its installed capacity during 6,596 hours of the year (75%). Highlighting that the diverse nature of Romania's power portfolio allows for much more supply throughout the year than countries with a more limited power supply mix.

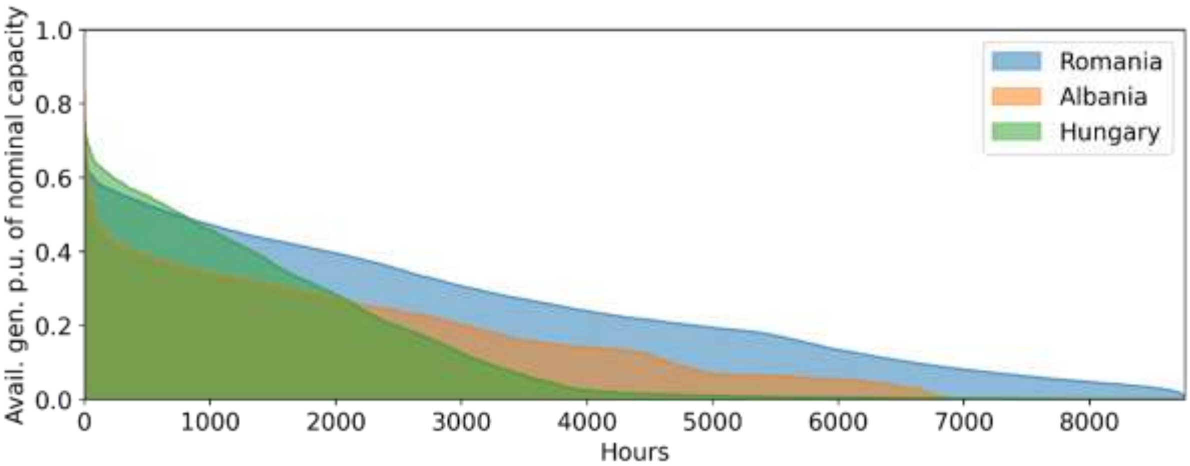

Figure 5.11 Duration curve of available generation per unit of nominal capacity for selected countries, Network 2050

Given that the model minimizes capital and operational costs for the whole European power system as a whole, different countries result in different technology configurations optimal to the system. These configurations are dependent on multiple factors programmed into the model, including regional and time-dependent resource availability, land availability, capacity factors, capital and operational cost of technologies, available transmission capacity, and electricity demand. This results in country configurations optimal for the European system as a whole but fails in many ways to resemble real-world national power systems, which in reality are also determined by other technical, economic, political, and social factors and interests, such as energy security, energy affordability, social acceptance, employment, and sustainable development goals. This results in either net-exporting or net-importing countries over the year, as absolute electricity trade is assumed by the model. Table 2.1 presents the import/export balance for the selected countries.

Table 5.1 Import/Export balance for selected countries, Network 2050 [GWh]

	Net Total imports	Net Exports	Balance
Romania	24,201.6	14,809.7	(-9,391.9)
Albania	361.5	18,809.7	18,448.2
Hungary	25,415.9	6,250.3	(-19,165.6)

Romania, even with its diverse generation portfolio, is a net importing country. Note that much of its imported electricity is justified by its cost, rather than its availability to produce electricity locally. As it is it mainly imports power during midday hours corresponding to cheaper solar energy elsewhere. In fact, out of the aggregated 6.37 TWh that Romania curtails over the year, 6.01 TWh (94.2%) are curtailed during periods when the country is net importing electricity. Nonetheless, its net exports are relatively high (14.8 TWh), second to Albania which has a much lower electricity demand and imports only 361 GWh over the year. This strongly suggests towards the benefits of combining solar and wave energy leveraging their complementary nature. On the other hand, Hungary is heavily dependent on electricity imports, both for satisfying its own electricity demand and for charging its storage technologies. Exports are also present, during peak solar days, but only represent 25.6% of what it imports over the year.

Relevant questions arise when dealing with cost-optimal configurations for such large power systems, even as Europe as a whole. On one hand, it is important to acknowledge that certain regions are endowed with different resources which can be exploited by existing renewable energy converters. Highlighting the importance to consider what that means for the energy-related and decarbonization European targets as they strive to be renewable energy leaders of the world, with ambitious targets towards 2050. While on the other hand, ensuring at a national level a degree of self-sufficiency, self-determination, economic development, and energy security and availability. These questions, however, go further than the scope of this research. Because of this, these results serve should serve more as a guiding post rather than as a roadmap for potentially future multi-renewable European power systems.

Regarding wave energy specifically, the forecasted costs estimated with the learning curve approach allowed for the cost-optimal deployment of WECs mainly in the Balkan region on the Black and Ionian Sea coastlines. The deployment of WECs in these locations was driven ultimately by cost-competitiveness specific to these regions., with multiple factors playing a role including land availability for specific renewables, cost of competing technologies, exploitable resource availability, and transmission expansion constraints. Wave energy potential in the Balck sea has been investigated by Rusu (2009). The author performed a medium-term wave analysis with in situ measured data, as well as implemented a wave prediction system based on the simulation waves near-shore model. It was concluded by his research that wave energy in the Black Sea has potential for development, particularly on its western side in the coastlines of Bulgaria and Romania, as assessed by the model of this research.

Transmission expansion is especially relevant towards the cost-optimal configurations of certain countries, particularly for the Balkan region, given cross-border capacity expansions in Eastern Europe were not prioritized by the model, seen in Figure 4.28 in the results overview of Network 2050 (section 4.3.7). This lack of transmission capacity to transport electricity from regions with higher solar and onshore wind resources, in combination with limited land availability for these technologies, ultimately results in the Eastern and Southeastern regions of Europe having more diverse configurations other than solar and wind, which translates to the highest average locational marginal prices (LMP), presented in Figure 5.12. These LMPs reflect the underlining configurations of each country, considering both their generated and imported electricity, and considering that they are optimized for the European system as a whole. The impacts of transmission expansion on the cost-optimal configuration of the system are further discussed in the following section.

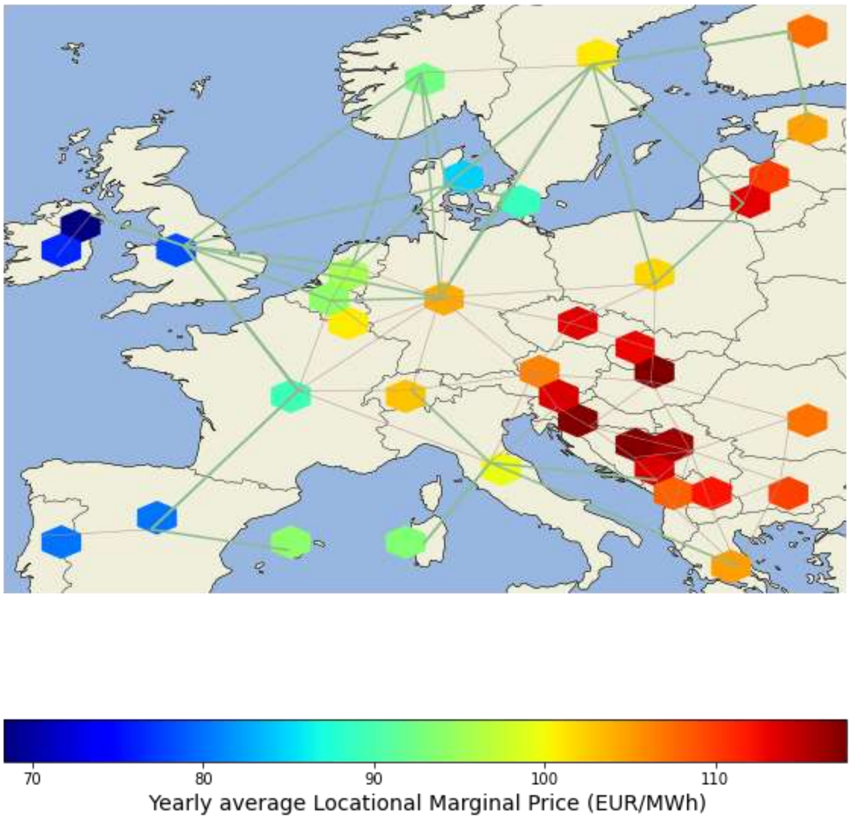

Figure 5.12 yearly average Locational marginal price for nodes, Network 2050

5.2 Transmission Expansion Sensitivity Analysis

As defined in the modeled scenarios of this research, a sensitivity analysis was performed on the allowed transmission expansion for Network 2050 to investigate the influence of transmission expansion constraints over the resulting cost-optimal configurations. In essence, the sum of all transmission line capacities multiplied by their respective lengths is constrained by CAP_{trans}. For the analysis, eight different expansion scenarios were modeled with gradual easement of the cap $CAP_{trans} = X_{const} \cdot CAP_{trans}^{today}$ with X_{const} = 1.00 (no expansion), 1.55, 1.75,, 2.0, 3.0, 4.5, 6.0 and optimal network, i,e. no constraint on transmission expansion.

Figure 5.13 plots relevant network parameters against allowed system expansion. The composition of the total system costs for all investments and operations of the optimized renewable power system as a function of the allowed transmission volume is plotted in Figure 5.13a. Total system costs exhibit a non-linear reduction as the constraint is eased, displaying initial rapid reductions and a tendency to plateau, reaching an economical optimal expansion at 4.5 times of CAP_{trans}^{today}. Note that even if the allowed system expansion was set at 6 times the existing capacity today, the model has already reached its economical optimal capacity expansion, and total system costs become insensitive to available expansion of transmission lines. Allowing the model to reach the optimal expansion of 4.5 times of today's cap provides an economic benefit of 68.46 billion Euros per year, although 78.5% of this benefit is already achieved at an expansion of two times the existing transmission network. These patterns have already been observed in detailed studies by Schlachtberger et al. (2017) and Schlachtberger et al. (2018).

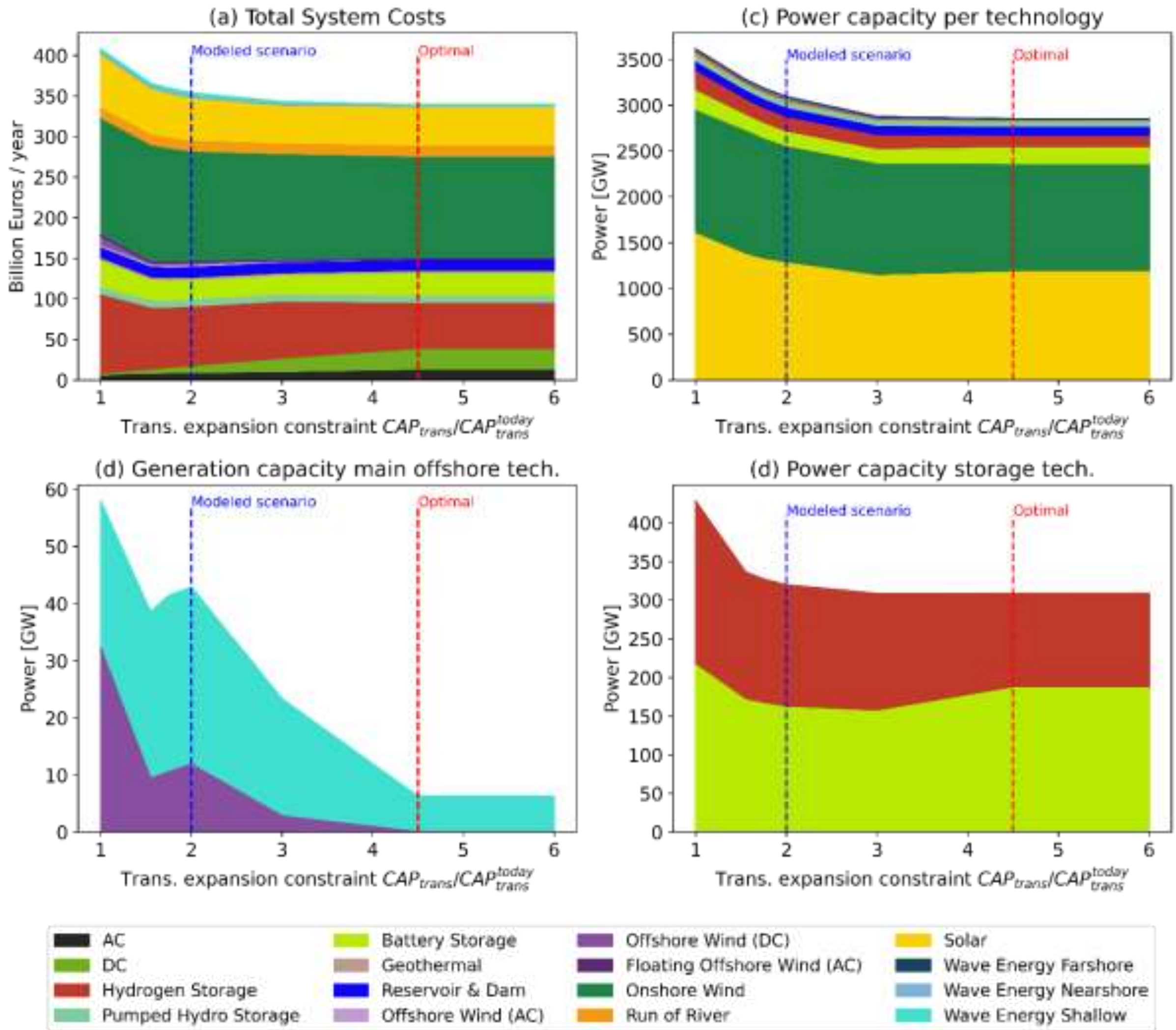

Figure 5.13 Total system costs (a), installed capacity (b), wave and offshore wind capacity (c), and storage power capacity (d) for different values of the transmission cap CAP_{trans}

Similar patterns are observed for the installed capacity of generating and storage technologies. From a cost-optimal system with today's existing capacities to the optimal expanded system, the installed capacity of solar and wind have the highest reduction in magnitude. However, these reductions of installed capacity also translate to reduced storage capacity, although as the system tends to an even more binary configuration of solar and wind, the share of battery and hydrogen storage capacity is modified, favoring the former, as seen in Figure 5.13 d. Ultimately, transmission capacity not only results in an economic benefit regarding the system costs but also a reduced need for installed generation capacity.

The model is sensitive to multiple other parameters due to its complexity, multiple data inputs, and different constraints. However, given the scope of this research as well as time constraints it was not practical to assess them. Through the modeled scenarios, as well as the transmission expansion sensitivity analysis, some of these sensitivities can be observed. Besides the transmission expansion constraints, the electricity demand which was scaled a for each of the modeled networks according to historical trends resulted in increases in the capacities of all technologies, but still initially prioritizing solar and onshore wind.

Nonetheless, if the analysis were to be performed at more distant horizons or if demand would grow at a faster rate, at some point, the geographic potentials of solar and onshore wind would be exhausted. The decline of solar and onshore wind installations would first be driven by the saturation of regions with high resource availability (high capacity factors) and high land availability, thus becoming less cost-effective to install. But the installations are ultimately limited by the geographic potentials estimated by the model given by the packing rate (MW/km^2) and land eligibility criteria (CORINE land use types, inclusion/exclusion of Natura 2000 protected areas, etc.) defined for each technology. This modelled constraint is more relevant at a regional level rather than at a European level. Coastline countries with available offshore resources have alternative generating renewable technologies to install, highlighting that on purely land availability criteria the wave energy resource is the most abundant within Europe, as estimated by the model with the inputted parameters and presented in section 4.2. However, the model does not provide alternatives for landlocked countries, where transmission expansion and electricity storage are the only alternatives for meeting increasing electricity demand.

Furthermore, the exogenously modeled potential cost reductions for wave energy converters, as well as the forecasted costs gathered from the JRC and the DEA, played a pertinent role in the cost-optimal configurations for the horizons 2030, 2040, and 2050. Specifically, the forecasted cost reductions of wave energy shallow estimated by the learning curve approach represented a cost-competitive advantage which translated into the deployment of this technology mainly in the coastlines of the Black and Ionian Seas, reaching 30 GW overall and meeting 75% of the 40 GW European ocean energy target by 2050. Nonetheless, the resulting configuration did not align with current trends and pledges for other offshore technologies, particularly as both bottom-fixed and floating wind were marginally installed. Highlighting that cost assumptions are one of the most significant sensitivities of the model.It is worth mentioning that offshore technologies have an extra cost burden within the model. Technology interconnection costs to the grid are only considered for offshore technologies, while they are considered negligible for onshore technologies. This is further discussed in the limitations section. Future research employing this model will seek to resemble better current trends and European targets on renewable energy with additional constraints, as purely cost-optimal runs in many ways fail to resemble real world power systems.

Lowering the costs of offshore wind would have a direct impact on the resulting cost-optimal renewable configurations of the system. Particularly impacting the deployment of wave energy, given the higher capacity factors of offshore wind observed in Figure 5.3. Ultimately it is dependent on the cost-effectiveness at a given location, but if offshore wind would be cheap enough, wave energy would mostly not be installed as offshore wind would be prioritized. This is an actual relevant challenge that wave energy faces into the future, as successful commercialization of WECs is not only dependent on technology readiness, which is still ongoing, but also on competing renewables' development trajectories, and how their costs and supply chains will develop. Nonetheless, there is strong potential for synergies among different offshore renewables, particularly on offshore energy infrastructure and technological learning. Furthermore, this research has highlighted the potential benefits of diversifying the renewable energy supply, and that it may be beneficial to have a variety of variable renewable generators, as it results in higher availability of supply and a reduction in its variability.

On other model sensitivities, Schlachtberger et al. (2018) document the sensitivity of the results to the chosen weather data, highlighting that the deployment of technologies that are affected by inter-annual variabilities, such as wave energy, is affected by the resource availability of the chosen year. Furthermore, the authors also found a variation in the results concerning the hourly resolution chosen, with increases in the share of solar power with a 3-hour resolution, attributed to the smoothening of fluctuations. They further highlight the sensitivity of the model to inputted capital costs, with solar and onshore wind capital costs having moderate influence over the modeling results, while decreases in storage technology costs have a weak influence over the results. Furthermore, Frysztacki et al. (2021b) highlight the strong effect that spatial resolution can have on modeling results, indicating that lower network resolution tends to underestimate total system costs, as network bottlenecks are ignored when clustering the system into single-country nodes.

The model further allows for additional constraints that can impact the optimization results and that were not applied in this research, such as CO_2 emission limits, capacity constraints on specific technologies, emission prices, and requiring nodes to produce a specific share of their own consumption, among others. Understanding the mechanisms and sensitivities of a model provides perspective into the cost-effective configurations of different technologies and modeling results. An important aspect to consider, especially when dealing with future energy system models, is that uncertainty and complexity are present. Ultimately, models of future electricity systems can provide relevant insights into cost-efficient energy portfolios and transmission

5.3 Limitations

The wide-ranging scope of the research, going from renewable resource assessments and power conversion functions to future technology cost projections and cost-optimal configurations, entails multiple limitations. Some relate to the wave energy resource addition, others to the input data, parameters, and constraints chosen for the optimization, and other limitations are attributed to the PyPSA model framework and are inherent to the PyPSA-Eur model.

Regarding the addition of wave energy to the model, only the metocean parameters of significant wave height (H_{m0}) and wave peak period (T_{peak}), in combination with the specific WEC power matrices, were employed to characterize a sea state and thus power generation potential. However, various other sea-state characteristics can influence the choice of an appropriate wave energy site. Wave direction is an important factor to consider for the optimal design and placement of wave energy devices. Places with low variability in direction may be preferable. Furthermore, other spectral properties of the sea state can also influence WEC power output and hence design (Fairley et al., 2020). This limitation is further highlighted by the fact that there has been no convergence of WEC designs, resulting in this research employing 3 different power matrices representing a design for different depths. Furthermore, the spatial resolution of the ERA5 database and the model (0.25°x0.25°) is not advised to perform wave energy analysis, particularly for nearshore and shallow wave energy converters (Guillou et al., 2020).

However, finding suitable high-fidelity datasets suitable for offshore applications is not common. It is expected that in the coming years i.e. 2025 the Marine Renewable Energies Lab (MREL) will publish the first high-resolution (500m) fully open-access wave database. Therefore, in absence of such a dataset, ERA5 was considered appropriate and used as default.

In addition, the optimization scenarios, of which resource assessments are part of the workflow, were performed with weather data only from the year 2018. However, to properly assess the wave energy resource, it is important to consider the monthly, seasonal, and annual variability of WEC performance. The International Electrotechnical Commission, recommends that a wave energy resource assessment should cover a minimum of ten years on a minimum temporal resolution of three hours. While the spatial resolution varies according to the stage of the project, reconnaissance, feasibility, or design stage (Guillou et al., 2020; IEC, 2014). This is further highlighted by the sensitivities of PyPSA-Eur model results to input weather data mentioned in the previous section and described by Schlachtberger et al. (2018).

From the original PyPSA-Eur framework and model, further limitations are still present. Firstly, PyPSA-Eur is a partial equilibrium model which only includes the power sector and does not consider sector coupling. However, an alternative version of the model, PyPSA-Eur-Sec, couples the existing model with the transport, heating, biomass, and industry sectors. Secondly, the use of Voronoi cells ignores the topology of the underlying distribution network, particularly at lower spatial resolutions. Voronoi cells are essentially nodal regions that are used as catchment areas for aggregated electricity loads, renewable resource potentials, technology capacities, etc. The use of the one-node per country approach in this research accentuates the impact of this limitation. Ultimately, this results in the model ignoring regional power grid bottlenecks and tends to underestimate costs (Frysztacki et al., 2021a). This country aggregation also can favor technology-exclusive configurations, e.g, fully onshore or fully solar, when a technology is more competitive (Victoria et al., 2020). Other PyPSA-Eur limitations include approximations made due to missing data and the topology of the ENTSO-E area; assumptions about the distribution of load proportional to population and GDP; and limited and missing information on existing power plants, including hydro. (Hörsch et al ,2018). In addition, transmission losses and ancillary services were not considered.

Furthermore, renewable generation technologies are modeled according to a single type of solar panel, turbine, or converter. Creating the need to define “new” technologies if multiple turbines or converters want to be considered, as it was done with wave and offshore wind. Furthermore, technology interconnection costs to the grid are only considered for offshore technologies, while they are considered negligible for onshore technologies. A reasonable assumption for practical purposes given that offshore technologies require offshore electricity infrastructure to operate. These costs are estimated based on the average distance from the node and installed capacity and are ultimately added to the capital cost of each specific technology. Nonetheless, placing additional economic burdens on offshore technologies independently impacts their cost-competitiveness during the optimization and fails to consider the potential synergies of shared infrastructure among offshore renewables. A potential alternative approach could be to allocate these offshore infrastructure costs directly on the transmission components of the model, rather than on the generating technologies independently, which may also better reflect the European Commission's policies and targets towards incentivizing the development of offshore renewable energy, such as the offshore grid corridors proposed in Trans-European Networks for Energy (TEN-E) policy (European Commission, 2022e).

Regarding energy storage, the model only optimizes battery and hydrogen energy storage, while PHS capacities are collected and remained fixed throughout the optimization. The chosen model of storage units in this research only optimizes power capacity, while energy capacity is a product of the energy-to-power ratio inputted as the maximum hours parameter for each technology. This is especially relevant for hydrogen, as optimized charging (electrolysis) and discharging (fuel cell) power capacities are one in the same. In reality, electrolysis and fuel cell capacities are independent of each other and do not need to be equivalent. Furthermore, overground steel tanks are assumed for hydrogen storage by the model. This assumption was kept from the original PyPSA-Eur cost assumptions and can be considered pessimistic as alternative forms of underground storage, including salt caverns and depleted oil & gas reservoirs. These alternatives offer a more cost-efficient way to store hydrogen but are not available everywhere (Bünger et al., 2016). Nonetheless, the assumption that all hydrogen is stored aboveground is a relevant limitation to the results. Lastly, hydrogen trade is not considered in the model and can only be utilized in the node where it is installed.

6. Conclusions and future outlook

This research performed an exploratory investigation of the potential role that wave energy can play in future, 100% multi-renewable, European power systems. This was achieved, first, by expanding the renewable energy capabilities of the existing open-source PyPSA-Eur, energy system model and dataset of the European power system at the transmission level covering the full ENTSO-E area, to include the wave energy resource. And second, by simulating a set of future, cost-optimal, and multi-renewable European power systems at 2030, 2040, and 2050 horizons employing a greenfield optimization approach and considering cost-reduction potentials of wave energy and other generating technologies. In this final section, the conclusions of this research are presented by revisiting the research questions formulated for the thesis.

What are suitable representative models and subroutines of wave energy converters to be integrated into the PyPSA framework and the PyPSA-Eur energy system model?

As an initial and foundational step for this research, the renewable energy capabilities PyPSA-Eur were expanded with the novel integration of a wave energy power conversion function that makes use of a wave energy converter's power matrix coupled with metocean data from the ERA5. Essentially, the model can now characterize a sea state at an hourly resolution and spatial resolution of 0.25° x 0.25° (approx.. 27.5 x 27.5km) with the parameters of significant wave height (H_{m0})and wave peak period (T_{peak}) gathered from the ERA5 dataset. By combining the characterized sea state with a specific WEC device power matrix, the equivalent of a wind turbine's power curve, an estimation of the power generation potential can be calculated. Three different WECs were integrated into the model: a Farshore 750kW representing an articulated attenuator type of converter, a 1 MW Nearshore device, corresponding to a point absorber device, and lastly a Shallow 600kW device operating in shallow waters representing a terminator surge-oriented device. Nonetheless, other power matrices representing different WECs can easily be added to the model, which is especially relevant given the multiple WEC prototypes and lack of convergence on an optimal design.

In combination with other existing parts of PyPSA-Eur, this addition allows to assess the wave energy resource across Europe's coastlines; estimate the renewable wave energy capacity potentials restricted by depth, packing rate, and land availability; Derive the renewable wave generation availability time series of specific WEC devices according to their power matrixes and the characterized sea-states; and consider the wave energy resource and technologies in a cost-based optimization of the European transmission grid.

What are the geographic energy potentials of wave energy in Europe considering different wave energy converters paired with climate and metocean conditions?

The novel integration of wave energy converters conversion functions paired with metocean data from ERA5 into the PyPSA framework allowed for the first power analysis software to assess the wave energy resource across Europe's coastlines. Within the model, geographic potential refers to the maximum installable capacity given the set of input parameters such as maximum and minimum depth, land eligibility restrictions, and packing rate (MW/km^2) for each device. In addition, given that the model computes the resource availability time series per unit of nominal capacity, the average yearly capacity factor of every grid cell for the year 2018 was calculated. By combining the geographic potential and the average capacity factor, an approximation of the total power generation potential was derived for each of the modeled devices.

Given the configured parameters and eligibility criteria for each device, their respective power matrix, and weather data from the year 2018, the model estimated a total European geographic potential of 20.3 TW, 14.7 TW, and 2.4 TW for the Farshore, Nearshore, and Shallow device, respectively. Great Britain has the highest potential for both the Farshore and Nearshore devices, with maximum installable capacities of 6.9 TW and 3.8 TW, respectively. As for the Shallow device, Sweden, Finland, and Denmark have the highest installable potentials with capacities close to 400 TW.

By combining the geographic potentials with the yearly average capacity factors by grid cell, the aggregated European power generation potential for the year 2018 was estimated at 23,840 TWh for the Farshore device, 9,642 TWh for the Nearshore device, and 2,533 TWh for the Shallow device. However, these estimations need to be taken with extreme caution, as this aggregation by grid cell ignores the potential power extraction from one grid cell to another and assumes the sea-state characteristics remain unchanged. Thus, this estimation serves better to identify locations with both extensive land availability and highly production sites, rather than as an aggregated technical resource estimation. At a regional level, the North Sea appears as the most promising location, particularly for the Farshore and Nearshore device, although some regions around Denmark, including the Baltic Sea, appear to be attractive for the Shallow Device.

In reality, the realized installed potential or practical resource depends on a variety of factors such as array types, WEC design, packing density, and marine spatial planning (i.e., colocation options) and require detailed assessment of local characteristics as well as the consideration of other wave properties, such as wave direction. Lastly, the potential exploitation of wave energy also depends on political, social, economic, and environmental factors implying a balance not only between land availability, but also conservation efforts, landscape impact, social acceptance, and political will.

> *How may the technology costs of wave energy converters develop by 2030, 2040, and 2050? What is their effect on cost-optimal configurations of a multi-renewable European power system?*

Given that the penetration of wave energy under the modeled future, cost-optimal, multi-renewable configurations of the European power system is highly dependent on its cost-competitiveness against other generating renewables, the potential future capital costs of the different wave energy converters were projected for the 2030, 2040 and 2050 horizons. The future technology costs for WECs were estimated through a one-factor learning curve approach. A learning curve is a mathematical representation of potential cost reductions attributed to technological learning processes. It expresses that the costs of technology decrease by a constant fraction with each doubling of the total number of units produced. A forecast of future wave energy capacity deployment was created based on offshore energy European targets outlined in the EU's offshore energy strategy, ocean energy industry targets, and the JRC's market study on ocean energy, reaching a total cumulative installed capacity of 40 GW by 2050. A variable learning rate of 12% between 2020 and 2030, 8% between 2030 to 2040, and 4% between 2040 and 2050 was used and it was assumed that cumulative WEC capacity over time provides the cost reduction benefit y learning to each device.

The Farshore device, with an initial capital cost of 4,500 €/kW, achieves a capital cost of 2,264 €/kW by 2030, 1,624 €/kW by 2040, and 1,475 €/kW by 2050. Meanwhile, the capital cost of the Nearshore device evolves from 3,000 €/kW in 2020 to 1,509 €/kW by 2030, 1,082 €/kW by 2040, and 983 €/kW by 2050. Similarly, the Shallow device, with an initial cost set at 2,500 €/kW, reaches a value of 1,258 €/kW by 2030, 902 €/kW by 2040, and 819 €/kW by 2050. These projected capital costs were inputted into the model exogenously and cost projections from the JRC and Danish Energy Agency were used for other generating renewables. These cost projections provided a cost-competitive advantage, particularly for the Shallow device, whose installed capacity grew from only 12.4 MW in the cost-optimal network modelled for the year 2030, to 26.4 GW in 2010, and 30.9 GW in 2050. The Shallow device was deployed mainly in the Balkan countries of Romania, Bulgaria, and Albania, as well as on the island of Sardinia in Italy. The cost-competitiveness of the Shallow device in these locations is attributed to the limited transmission capacity and limited land availability of these countries

In reality, the development of wave energy still faces technical and non-technical challenges. WECs find themselves at different levels of TRLs given the various designs and prototypes, with many of them undergoing testing at TRL 7. With long-term survivability and high capital costs representing some key challenges. Given this, uncertainty remains about whether they will achieve commercialization, even if this is the closest they have gotten. The rapid rise of other renewables, including other ocean renewables like offshore wind and tidal, also represents a commercial challenge, as they have demonstrated higher levels of technology readiness as well as demonstrated commercial application. Increased national support strategies and market incentives can strongly influence the development of wave energy technology, highlighting the various benefits it can provide, such as support in decarbonization goals, diversifying the energy mix and increased energy security, environmental benefits, etc.

> *What are the general system dynamics of a multi-renewable European power system which considers the deployment of wave energy converters? And how do the network components evolve through the 2030, 2040, and 2050 horizons?*

From an overall system perspective, the modelled 2030, 2040, and 2050 cost-optimal configurations of the European network were very similar. Solar and onshore wind dominated the deployed generating technologies installed extensively across Europe representing between 48-47% and 45-47% respectively of the overall generation mix across the different horizons. Total installed generating capacity grew from 2.37 TW in network 2030 to 2.72 TW in network 2050, following the increased electricity demand over the horizons. Wave energy shallow and offshore wind (DC) where the two offshore technologies most widely deployed. WEC Shallow cost reductions provided a cost-competitive advantage in some locations as its capacity grew from only 12 MW in 2030 up to 30.9 GW in 2050 and was installed mainly in the Black and Mediterranean Seas. Offshore wind (DC) was essentially only installed in Romania in the Black Sea with a capacity of around 11.8GW and remained relatively constant throughout the horizons. Other offshore energy converters were minimally installed with total installed capacities in the order of magnitude of MW with a combined share of less than 0.04% of the total deployed capacity. Although these results almost satisfy the 40 GW specific target of ocean energy in the EU Strategy on Offshore Renewable Energy, they fall extremely short of the overall target of 300 GW of offshore energy by 2050 with only 42.8 GW of aggregated offshore capacity by 2050.

The dominance of solar and wind determine the behavior of the overall system, with available generation throughout the year characterized by diurnal patterns, peaking during midday. The wide deployment of these two technologies also determines the type of storage installed in different locations. It was found that solar installed capacity has a moderately strong correlation with installed battery capacity, while onshore wind capacity is strongly correlated with installed hydrogen storage capacity. This highlights the need for short-term storage paired with solar generation and long-term storage with onshore wind generation.

At a regional level, Romania, Albania, and Hungary's configurations were compared against each other, chosen based on their HHI, similar aggregated generation capacity, and their share of wave energy capacity. Romania is the country with the most diversified generation portfolio with an HHI value of 0.27. Interestingly, Romania is also the country with the least amount of storage capacity. However, no correlation was found between a multi-renewable energy portfolio and storage capacity needs. Meanwhile, Albania's portfolio consists of approximately equal parts of solar and wave energy, while Hungary has a solar-dominant generation portfolio (96%). Romania was found to be the country with the most stable available supply of electricity throughout the year, however, it significantly imports electricity during midday hours. It was found that it is actually importing cheaper electricity from elsewhere, most likely solar, given the time of the day, and curtailing its own, more expensive, electricity generation. Albania highlighted the potential benefits of solar and wave energy combined, given their complementary nature of supply. It is also a relevant net exporter of electricity for the region, exporting 52 times the amount of imported electricity. Lastly, Hungary is heavily dependent on electricity imports, both for satisfying its own electricity demand and for charging its storage technologies, and only exporting during peak solar generation periods.

> *What is the impact of transmission capacity expansion under cost-optimal configurations of a multi-renewable European power system?*

A sensitivity analysis was performed on the allowed transmission expansion for Network 2050 to investigate the influence of transmission expansion constraints over the resulting cost-optimal configurations. It was found that total system costs and the total installed capacity of generation and storage exhibit a non-linear reduction as the constraint is eased, displaying initial rapid reductions and a tendency to plateau, reaching an economical optimal expansion at 4.5 times of today's existing transmission capacity. Allowing the model to reach the optimal expansion of 4.5 times of today's capacity provides an economic benefit of 68.46 billion Euros per year, although 78.5% of this benefit is already achieved at an expansion of two times the existing transmission network. Furthermore, as transmission expansion constraints are eased, both wave energy shallow and offshore wind (DC), the two offshore technologies most widely installed are significantly reduced, with offshore wind being fully displaced. This is attributed to the fact that cheaper solar and onshore wind electricity can now be transferred to the locations where these offshore technologies were installed. It is important to note that these patterns had already been studied by Schlachtberger et al. (2017) and Schlachtberger et al. (2018).

> *What is the potential role of wave energy in future cost-optimal configurations of the European transmission network under a multi-renewable power system?*

The future development of wave energy is still uncertain as it still faces relevant challenges toward successful commercialization. Nonetheless, it is a vast and untapped resource that has the technical potential to meet a significant share of global energy needs. It is considered a high energy-dense and predictable resource characterized by high availability, that can play an important role in achieving carbon emission reduction targets while supplying energy demand.

However, many of the most valuable benefits explored in this research are not inherent to wave power technology in itself, but rather to its inclusion in multi-renewable energy portfolios. Multi-renewable energy portfolios can play an important role in achieving carbon emission reduction targets while supplying energy demand, broadening the energy mix, increasing the availability of renewable power, enhancing energy security, and potentially providing multiple economic and social benefits through industry and job creation. As was presented in this research, wave energy technologies can be integrated with other renewable generators to provide higher availability of supply, smoothen the power output reduce the variability, and increases the consistency of the regional generation profile.

Capacity transmission plays a critical role in enabling our ability to capture most of the potential benefits brought by variable renewable generation. Given that different regions are endowed with different exploitable renewable resources, it is important to leverage the strengths of regions with high resource availability. For Europe as a whole, the renewable energy transition supports decarbonization targets, increases the diversity of the energy mix, and reduces the import dependency of energy, enhancing overall energy security. However, this raises relevant questions about the future European power system and its energy-related and decarbonization targets., particularly as they strive to be renewable energy leaders of the world, with ambitious targets towards 2050. On the other hand, it is critical for European countries, at a national level, to ensure a degree of self-sufficiency, self-determination, economic development, and energy security. These questions, however, go further than the scope of this research. Nonetheless, the modified PyPSA-Eur, and power system modeling in general, are valuable tools to assess cost-optimal configurations of multi-renewable power portfolios, while also optimizing interactions of renewable power among different regions.

6.1 Research Contribution and Future Outlook

The present research contributes to the existing body of scientific research on future renewable power systems, power system analysis, and wave energy integration. It builds on prior work developed by Hörsch et al., (2018a), specifically by employing and further expanding the PyPSA-Eur power system model developed with the PyPSA toolbox. The main contribution of this research was the expansion of the model's renewable energy assessment capabilities to include the wave energy resource. This addition allows for the assessment of the wave energy resource across Europe's coastlines, estimation of the renewable wave energy capacity potentials, determination of the renewable wave generation availability time series according to specific wave energy converters and metocean data, and the consideration of wave energy technology in future investment, planning, and operational studies of the European power system. This represents a valuable addition to better understand and explore potential configurations of future renewable power systems aligned with decarbonization targets, making it not only scientifically relevant but socially and politically relevant also. It is hoped that this addition will enable further investigations and discussions of future renewable power systems and the potential role of wave energy.

Additionally, the results of this research allowed to identify potential development pathways of wave energy converters by employing a learning curve approach to identify potential cost reductions of wave energy converters. Furthermore, relevant insights about the potential benefits of multi-renewable energy portfolios were found, including higher power availability and consistency, highlighting their relevance towards continental and national energy security. The research further provides future cost-optimal configurations for the European power system, optimized as a whole, and identifies least-cost solutions to a fully renewable power system, which now considers the wave energy resource. These results can serve not only as case studies, but also as recommendations for the future European power system, highlighting that cross-border transmission capacity is a cost-effective investment that supports the system's ability to capture and fully take advantage of renewable energy resources unevenly distributed across Europe.

Future work can be conducted for a multitude of purposes. The model can be further expanded to include other ocean technologies such as tidal energy and OTEC. Meanwhile, further research can be conducted on smaller geographical scopes (national level) and higher spatial resolution to further investigate the wave energy resource, and other renewables, in specific countries. Future research can further investigate configurations aligned with the European Commission's renewable and offshore energy targets, given that the purely cost-optimal configurations in this research failed to resemble this target in some ways. This can be achieved by including additional constraints to the model, such as a minimum capacity for each type of generator or a requirement that each country should produce a minimal share of its consumption. The open-source and transparent nature of PyPSA-Eur allows for further improvements and investigations as novel data or information becomes available.

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8. Appendix

8.1 Generation Capacities Results

Table 8.1 Optimized capacities of generators by country for the 2030 Network [MW]

Countries	Solar	Onshore Wind	Offshore Wind (DC)	Offshore Wind (AC)	Floating Offshore Wind (AC)	Wave Energy Farshore	Wave Energy Nearshore	Wave Energy Shallow	Geothermal	Reservoir & Dam	Run of River	Total Countries
France	135,611.46	256,797.09	0.37	0.41	0.23	0.08	0.21	0.38		8,795.51	5,791.55	**406,997.3**
Italy	230,740.72	72,137.94	0.32	0.54	0.33	0.14	0.20	1.60	800.00	4,177.83	6,563.71	**314,423.3**
Germany	156,626.11	101,555.64	0.70	0.56	0.07	0.11	0.14	0.32		189.50	2,997.03	**261,370.2**
United Kingdom	266.18	173,927.87	0.62	0.53	0.26	0.13	0.29	0.72		463.50	685.20	**175,345.3**
Spain	105,700.42	54,841.26	0.26	0.42	0.29	0.20	0.34	0.65		8,338.04	16.40	**168,898.3**
Poland	31,802.94	127,236.19	0.57	0.36	0.19	0.06	0.11	0.38		308.02	14.40	**159,363.2**
Netherlands	45,863.26	46,233.49	0.30	0.36		0.10	0.11	0.41				**92,098.0**
Denmark	3.85	72,132.57	0.62	0.59	0.34	0.16	0.18	0.62				**72,138.9**
Czech Republic	64,775.55	838.45								688.98	40.23	**66,343.2**
Sweden	23,961.75	28,562.04	0.44	0.31	0.12	0.03	0.04	0.32		11,425.76	1,955.86	**65,906.7**
Austria	54,867.33	1.69								6,139.10	4,478.51	**65,486.6**
Greece	43,130.31	19,247.57	0.64	0.27	0.16	0.04	0.11	0.58		2,593.20	103.10	**65,076.0**
Finland	5,154.32	50,356.28	0.30	0.29	0.17	0.04	0.07	0.26		1,489.90	1,289.60	**58,291.2**
Switzerland	41,422.01	0.38								9,867.50	5,269.34	**56,559.2**
Belgium	35,372.80	15,344.95	0.39	0.36			0.13	0.33		12.74	59.02	**50,790.7**

Countries	Solar	Onshore Wind	Offshore Wind (DC)	Offshore Wind (AC)	Floating Offshore Wind (AC)	Wave Energy Farshore	Wave Energy Nearshore	Wave Energy Shallow	Geothermal	Reservoir & Dam	Run of River	Total Countries
Portugal	36,169.59	4.57		0.30	0.18	0.11	0.25	0.38	28.80	2,215.40	1,615.50	**40,035.1**
Norway	1,293.31	1,890.34	0.69	0.35	0.13	0.05	0.19	0.42		31,692.04		**34,877.5**
Romania	127.62	8,967.72	11,734.90	2.53	0.27	0.07	0.12	0.59		5,303.48	870.45	**27,007.7**
Hungary	13,528.67	11,576.03								28.00	19.70	**25,152.4**
Bulgaria	18,391.00	4,151.18	0.10	0.47	0.21	0.08	0.12	0.88		1,484.50	22.40	**24,050.9**
Serbia	14,632.63	6,131.25										**20,763.9**
Croatia	14,591.47	817.77	0.44	0.46	0.17	0.02	0.02	0.17		1,322.40	278.67	**17,011.6**
Ireland	7,698.11	8,385.84	0.30	0.31	0.16	0.05	0.21	0.46		1.00	216.00	**16,302.4**
Slovakia	14,591.07	2.28								792.00	641.33	**16,026.7**
Albania	15,245.41	0.58		0.18	0.12	0.05	0.09	1.98				**15,248.4**
Bosnia and Herzegovina	9,064.54	0.48										**9,065.0**
Lithuania	6,595.47	1,677.79	0.58	0.44	0.21	0.07	0.12	0.22		101.00		**8,375.9**
Estonia	884.09	7,485.16	0.33	0.29	0.16	0.06	0.09	0.22				**8,370.4**
FYR of Macedonia	6,540.41	0.24								533.00	41.60	**7,115.2**
Slovenia	4,237.19	0.75		0.15			0.03	0.05		730.79	861.34	**5,830.3**
Luxembourg	2,481.82	3,046.43									30.90	**5,559.1**
Latvia	573.86	3,024.16	0.55	0.39	0.20	0.07	0.11	0.35		869.00	642.10	**5,110.8**
Montenegro	5,021.11	0.34		0.12	0.11	0.05	0.07	0.15				**5,022.0**
Total	**1,146,966**	**1,076,376**	**11,743.4**	**11.0**	**4.1**	**1.8**	**3.3**	**12.4**	**828.8**	**99,562.2**	**34,503.9**	**2,370,013**

Table 8.2 Optimized capacities of generators by country for the 2040 Network [MW]

Countries	Solar	Onshore Wind	Offshore Wind (DC)	Offshore Wind (AC)	Floating Offshore Wind (AC)	Wave Energy Farshore	Wave Energy Nearshore	Wave Energy Shallow	Geothermal	Reservoir & Dam	Run of River	Total Country

France	140,722.	274,423.97	0.43	0.48	0.49	0.11	0.37	0.64		8,795.51	5,791.55	429,735.7
Italy	251,088.82	73,120.35	0.38	0.60	0.55	0.23	0.35	6,378.66	800.00	4,177.83	6,563.71	342,131.5
Germany	186,317.01	84,797.52	0.66	0.67	0.10	0.17	0.22	0.51		189.50	2,997.03	274,303.4
United Kingdom	6.88	219,595.51	0.70	0.63	0.48	0.24	0.47	1.15		463.50	685.20	220,754.7
Poland	30,057.03	151,895.19	0.73	0.43	0.35	0.10	0.16	0.74		308.02	14.40	182,277.2
Spain	108,613.45	60,728.01	0.24	0.50	0.48	0.32	0.54	1.33		8,338.04	16.40	177,699.3
Netherlands	45,863.49	46,233.51	0.36	0.42		0.15	0.18	0.79				92,098.9
Sweden	23,054.68	38,452.02	0.55	0.42	0.28	0.06	0.08	0.54		11,425.76	1,955.86	74,890.2
Denmark	4.65	72,132.59	0.85	0.75	0.66	0.25	0.31	1.08				72,141.1
Czech Republic	68,841.91	5.99								688.98	40.23	69,577.1
Greece	46,909.81	17,676.69	0.67	0.31	0.26	0.07	0.16	1.40		2,593.20	103.10	67,285.7
Austria	54,867.41	2.21								6,139.10	4,478.51	65,487.2
Finland	1,505.54	57,230.76	0.34	0.34	0.29	0.09	0.14	0.39		1,489.90	1,289.60	61,517.4
Switzerland	41,422.06	0.44								9,867.50	5,269.34	56,559.3
Belgium	35,372.91	15,344.95	0.43	0.41			0.21	0.58		12.74	59.02	50,791.2
Portugal	44,175.38	3.73		0.34	0.31	0.18	0.42	0.68	28.80	2,215.40	1,615.50	48,040.7
Norway	345.43	6,949.02	0.93	0.41	0.25	0.12	0.21	0.76		31,692.04		38,989.2
Romania	371.91	11,375.34	9,606.05	2.76	0.74	0.11	0.18	2,596.40		5,303.48	870.45	30,127.4
Bulgaria	18,800.56	36.26	0.10	0.50	0.41	0.13	0.19	9,116.91		1,484.50	22.40	29,462.0
Hungary	21,556.75	5,977.59								28.00	19.70	27,582.0
Albania	10,984.91	0.57		0.19	0.19	0.08	0.14	8,265.62				19,251.7
Slovakia	16,348.90	2.22								792.00	641.33	17,784.4
Serbia	16,606.12	16.28										16,622.4
Ireland	3,205.77	9,520.93	0.38	0.36	0.31	0.11	0.33	0.81		1.00	216.00	12,946.0
Croatia	10,771.00	69.59	0.50	0.54	0.25	0.03	0.05	0.27		1,322.40	278.67	12,443.3

Bosnia and Herzegovina	11,503.45	0.57										11,504.0
Estonia	811.49	8,837.99	0.39	0.33	0.25	0.09	0.13	0.34				9,651.0
Lithuania	6,067.55	1,719.09	0.68	0.51	0.38	0.11	0.18	0.38		101.00		7,889.9
FYR of Macedonia	6,585.36	0.28								533.00	41.60	7,160.2
Latvia	2,574.86	2,095.40	0.63	0.45	0.40	0.11	0.17	0.64		869.00	642.10	6,183.7
Luxembourg	2,481.84	3,046.41									30.90	5,559.1
Montenegro	5,020.93	0.39		0.15	0.18	0.07	0.10	0.28				5,022.1
Slovenia	21.84	0.86		0.20			0.04	0.08		730.79	861.34	1,615.2
Total technology	1,212,881.9	1,161,292.2	9,616.0	12.7	7.6	2.9	5.3	26,371.0	828.8	99,562.2	34,503.9	2,545,084.5

Table 8.3 Optimized capacities of generators by country for the 2050 Network [MW]

Countries	Solar	Onshore Wind	Offshore Wind (DC)	Offshore Wind (AC)	Floating Offshore Wind (AC)	Wave Energy Farshore	Wave Energy Nearshore	Wave Energy Shallow	Geothermal	Reservoir & Dam	Run of River	Total Country
France	168,022.4	289,735.21	0.49	0.54	0.55	0.27	0.69	0.80		8,795.51	5,791.55	472,348.0
Italy	252,415.0	81,672.95	0.46	0.69	0.66	0.40	0.61	6,929.41	800.00	4,177.83	6,563.71	352,561.8
United Kingdom	6.18	274,253.82	0.86	0.78	0.65	0.43	0.79	1.45		463.50	685.20	275,413.6
Germany	202,071.7	69,166.47	0.71	0.89	0.10	0.24	0.33	0.65		189.50	2,997.03	274,427.6
Poland	29,953.08	174,921.83	0.97	0.53	0.41	0.15	0.23	0.97		308.02	14.40	205,200.6
Spain	111,298.99	70,728.50	0.33	0.59	0.55	0.48	0.85	2.73		8,338.04	16.40	190,387.5
Netherlands	45,863.39	46,233.50	0.40	0.49		0.22	0.34	1.00				92,099.3
Sweden	19,480.78	48,620.91	0.70	0.54	0.36	0.11	0.17	0.67		11,425.76	1,955.86	81,485.9
Denmark	5.96	72,132.63	1.11	0.95	0.85	0.36	0.56	1.41				72,143.8

Countries	Solar	Onshore Wind	Offshore Wind (DC)	Offshore Wind (AC)	Floating Offshore Wind (AC)	Wave Energy Farshore	Wave Energy Nearshore	Wave Energy Shallow	Geothermal	Reservoir & Dam	Run of River	Total Country
Czech Republic	69,573.33	5.07								688.98	40.23	70,307.6
Greece	50,247.49	17,247.83	0.76	0.36	0.30	0.16	0.23	1.97		2,593.20	103.10	70,195.4
Finland	238.42	63,841.84	0.39	0.40	0.33	0.19	0.30	0.47		1,489.90	1,289.60	66,861.8
Austria	54,867.33	2.74								6,139.10	4,478.51	65,487.7
Switzerland	41,422.03	0.51								9,867.50	5,269.34	56,559.4
Belgium	35,371.25	15,344.95	0.48	0.46			0.30	0.72		12.74	59.02	50,789.9
Portugal	44,175.28	4.07		0.39	0.35	0.26	0.75	0.86	28.80	2,215.40	1,615.50	48,041.7
Norway	16.94	6,856.29	1.44	0.52	0.46	0.21	0.45	1.00		31,692.04		38,569.3
Hungary	30,865.10	1,175.76								28.00	19.70	32,088.6
Romania	1,458.51	9,674.57	11,842.56	4.16	0.83	0.18	0.27	2,596.44		5,303.48	870.45	31,751.4
Bulgaria	19,538.19	52.74	0.12	0.60	0.45	0.18	0.29	9,873.04		1,484.50	22.40	30,972.5
Albania	12,976.09	0.64		0.22	0.21	0.12	0.21	11,552.73				24,530.2
Serbia	20,094.68	10.14										20,104.8
Slovakia	16,913.62	2.50								792.00	641.33	18,349.5
Croatia	10,281.30	398.62	0.61	0.67	0.35	0.08	0.09	0.33		1,322.40	278.67	12,283.1
Estonia	430.29	10,097.17	0.48	0.39	0.29	0.13	0.19	0.42				10,529.4
Bosnia and Herzegovina	9,863.13	0.67										9,863.8
Ireland	908.34	8,456.87	0.45	0.41	0.39	0.18	0.56	0.99		1.00	216.00	9,585.2
Lithuania	5,922.00	2,113.39	0.85	0.60	0.47	0.15	0.26	0.48		101.00		8,139.2
FYR of Macedonia	6,852.47	0.32								533.00	41.60	7,427.4
Latvia	3,176.37	1,844.19	0.74	0.53	0.46	0.16	0.24	0.81		869.00	642.10	6,534.6
Luxembourg	2,481.79	3,046.17									30.90	5,558.9
Montenegro	5,020.41	0.45		0.17	0.20	0.11	0.16	0.35				5,021.8
Slovenia	1,365.48	1.02		0.24			0.06	0.10		730.79	861.34	2,959.0

Countries	Solar	Onshore Wind	Offshore Wind (DC)	Offshore Wind (AC)	Floating Offshore Wind (AC)	Wave Energy Farshore	Wave Energy Nearshore	Wave Energy Shallow	Geothermal	Reservoir & Dam	Run of River	Total Country
Total	1,273,177	1,267,644	11,854.9	16.1	9.2	4.7	8.9	30,969.8	828.8	99,562.2	34,503.9	2,718,580

8.2 Storage Capacities Results

Table 8.4 Optimized power capacities of storage technology by country for the 2030 Network [MW]

Countries	Battery Storage	Hydrogen Storage	Pumped Hydro Storage	Total country
Italy	46,902.4	279.2	7,787.4	54,969.0
France	12,106.2	22,365.7	5,289.0	39,760.9
United Kingdom	8.5	31,120.9	2,833.0	33,962.4
Spain	20,510.4	9.5	8,144.2	28,664.1
Germany	379.2	18,885.4	7,096.4	26,361.0
Netherlands	9.9	15,305.1		15,315.1
Czech Republic	6,821.5	5,189.3	1,195.0	13,205.8
Greece	10,415.0	1,204.9	699.0	12,318.8
Poland	46.4	10,346.8	1,793.2	12,186.5
Austria	7,788.9	2.8	4,241.3	12,033.1
Switzerland	8,075.6	3.4	3,848.8	11,927.7
Portugal	7,633.5	0.6	2,931.5	10,565.5
Belgium	447.4	8,149.1	1,307.5	9,904.0
Denmark	572.2	5,240.8		5,813.0
Finland	90.1	4,795.6		4,885.7
Albania	4,101.2	349.5		4,450.6
Hungary	2,596.8	1,072.4		3,669.2
Ireland	1,144.4	1,904.0	342.0	3,390.4
Croatia	640.4	1,812.5	518.7	2,971.6

Countries	Battery Storage	Hydrogen Storage	Pumped Hydro Storage	Total country
Serbia	2,746.5	20.3		2,766.8
Sweden	1,857.1	407.1	426.0	2,690.1
Luxembourg	5.0	1,205.6	1,291.0	2,501.5
Bulgaria	608.7	113.6	1,399.0	2,121.4
Slovenia	484.2	961.6	185.0	1,630.7
Lithuania	424.2	252.1	900.0	1,576.3
FYR of Macedonia	1,171.3	294.2		1,465.6
Slovakia	387.7	13.1	1,021.3	1,422.0
Montenegro	1,272.6	80.2		1,352.8
Norway	4.5	0.8	1,344.3	1,349.6
Bosnia and Herzegovina	1,189.1	25.2		1,214.3
Estonia	198.9	958.0		1,156.9
Romania	628.3	221.6		849.8
Latvia	108.2	8.1		116.3
Total	**141,376.0**	**132,599.0**	**54,593.6**	**328,568.6**

Table 8.5 Optimized power capacities of storage technology by country for the 2040 Network [MW]

Countries	Battery Storage	Hydrogen Storage	Pumped Hydro Storage	Total country
Italy	50,688.9	95.5	7,787.4	58,571.8
France	8,629.3	23,892.8	5,289.0	37,811.1
United Kingdom	10.1	38,145.8	2,833.0	40,988.9
Spain	22,944.6	8.3	8,144.2	31,097.0
Germany	3,755.4	17,978.2	7,096.4	28,830.1
Netherlands	47.4	16,704.6		16,752.0
Czech Republic	6,473.9	4,880.6	1,195.0	12,549.4
Greece	11,346.4	1,056.6	699.0	13,102.0
Poland	1,278.5	11,647.7	1,793.2	14,719.4

Countries	Battery Storage	Hydrogen Storage	Pumped Hydro Storage	Total country
Austria	5,084.3	4.0	4,241.3	9,329.7
Switzerland	11,719.1	7.4	3,848.8	15,575.3
Portugal	10,180.5	0.9	2,931.5	13,112.9
Belgium	46.8	6,956.9	1,307.5	8,311.2
Denmark	2,031.7	7,417.9		9,449.7
Finland	52.5	5,224.1		5,276.6
Albania	2,074.4	760.4		2,834.7
Hungary	4,233.3	316.6		4,549.9
Ireland	682.0	1,568.5	342.0	2,592.5
Croatia	40.9	1,432.8	518.7	1,992.4
Serbia	2,760.6	68.7		2,829.3
Sweden	1,178.8	1,239.6	426.0	2,844.3
Luxembourg	13.4	1,078.1	1,291.0	2,382.5
Bulgaria	811.3	102.7	1,399.0	2,313.0
Slovenia	13.5	697.2	185.0	895.7
Lithuania	234.4	564.4	900.0	1,698.8
FYR of Macedonia	754.4	493.9		1,248.3
Slovakia	162.0	34.4	1,021.3	1,217.7
Montenegro	1,255.8	43.2		1,299.0
Norway	6.4	1.8	1,344.3	1,352.5
Bosnia and Herzegovina	2,494.5	366.2		2,860.7
Estonia	127.3	1,065.0		1,192.3
Romania	89.6	49.6		139.3
Latvia	173.1	15.4		188.5
Total	151,395.2	143,919.7	54,593.6	349,908.4

Table 8.6 Optimized power capacities of storage technology by country for the 2050 Network [MW]

Countries	Battery Storage	Hydrogen Storage	Pumped Hydro Storage	Total country
Italy	49,561.3	1,308.8	7,787.4	58,657.4
United Kingdom	15.3	47,092.5	2,833.0	49,940.8
France	12,962.3	27,751.2	5,289.0	46,002.5
Spain	23,173.2	6.8	8,144.2	31,324.1
Germany	4,049.8	14,344.3	7,096.4	25,490.5
Netherlands	63.1	16,562.8		16,625.9
Poland	2,067.2	12,607.1	1,793.2	16,467.6
Switzerland	12,564.4	12.0	3,848.8	16,425.1
Greece	12,030.5	1,076.8	699.0	13,806.2
Denmark	2,904.2	10,220.2		13,124.3
Portugal	9,770.9	1.1	2,931.5	12,703.5
Czech Republic	6,231.9	4,892.1	1,195.0	12,319.1
Austria	5,494.5	4.4	4,241.3	9,740.2
Belgium	32.1	6,996.6	1,307.5	8,336.2
Hungary	6,603.5	56.1		6,659.6
Finland	66.4	5,925.5		5,991.9
Albania	2,811.1	814.3		3,625.4
Serbia	2,761.0	460.1		3,221.1
Bosnia and Herzegovina	2,668.0	277.7		2,945.7
Bulgaria	1,300.4	24.9	1,399.0	2,724.3
Sweden	473.5	1,798.5	426.0	2,698.0
Luxembourg	15.7	1,011.7	1,291.0	2,318.4
Croatia	316.9	1,276.5	518.7	2,112.2
Ireland	414.3	1,137.8	342.0	1,894.1
Lithuania	63.8	653.6	900.0	1,617.4
Norway	10.6	2.2	1,344.3	1,357.1
Estonia	76.9	1,273.9		1,350.8

Countries	Battery Storage	Hydrogen Storage	Pumped Hydro Storage	Total country
FYR of Macedonia	881.9	399.3		1,281.2
Slovakia	199.9	33.4	1,021.3	1,254.5
Montenegro	1,210.5	26.6		1,237.0
Slovenia	30.8	536.6	185.0	752.4
Latvia	151.9	19.9		171.8
Romania	120.0	9.2		129.2
Total	161,097.6	158,614.4	54,593.6	374,305.5