

Network Representation on Hydrogen Production Siting

A controlled comparison of electricity grid and
hydrogen network modelling
in the North Sea region

Master Thesis Complex Systems Engineering and
Management

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Preface

My interest in hydrogen and its place in the wider energy system grew during the Complex Systems Engineering and Management programme. That is what led me to the question of where hydrogen should be produced in the North Sea, and with the help of my supervisors it developed into something more interesting: how much that answer depends on the way the network is represented in the model. Five months of work later, I am proud that this thesis closes my studies with everything I have worked on along the way coming together in one project.

I would like to thank my supervisors. Kenneth Bruninx, your knowledge of electricity systems and network physics shaped this project from the start. You were closely involved throughout, and the detail of your feedback, on the model, the formulation, and the writing, is a large part of why this thesis holds together. Aad Correljé, thank you for keeping the work pointed at the real problem and societal relevance. When I disappeared into the details of the model you asked what it was actually for, and your broader view of energy and gas systems kept the project pointed at the question it was meant to answer. Laurens Frowijn, thank you for being available whenever I needed it, and for offering help wherever you could. Your practical advice on modelling and writing, and your willingness to think along at short notice, made the process considerably smoother than it would otherwise have been.

I would also like to thank the developers of the Tulipa Energy Model at TNO. The meetings and the tips along the way were valuable, and it helped a great deal to be able to ask questions directly of the people building the framework. I appreciated the genuine interest you took in the project.

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*Teije Heutink
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Summary

Europe is expanding offshore wind in the North Sea at large scale to meet its climate targets and strengthen energy security. This power is generated far from where energy is used and does not always match demand. Converting part of it into hydrogen is one way to manage that mismatch, since hydrogen can be stored, moved through pipelines, and used in sectors that are hard to electrify. Where to build the electrolyzers is a central design question. Offshore wind power can be transmitted to land by cable and converted to hydrogen onshore, or it can be converted to hydrogen at the wind farms and transported through pipelines to shore. The choice determines which transmission infrastructure must be built, and that infrastructure is costly and hard to change, so the decision shapes the North Sea system for decades.

Studies of the North Sea energy system disagree on where this hydrogen should be produced. Some find onshore production cheapest and others find offshore cheapest, and the disagreement is patterned. Part of it can be traced to modelling choices, and one of those is how the model represents the electricity grid and the hydrogen network. This is not the question a study asks or an uncertain value it could vary, but a structural feature that sets which physics the model can express. No earlier study has isolated its effect on where hydrogen is produced. This thesis addresses that gap. The main research question is: how do electricity grid and hydrogen network representations in an energy system model influence the cost-optimal location and configuration of hydrogen production in the North Sea region?

To answer this, a cost-minimising model of the North Sea energy system was built. It selects where to invest in electrolyzers, cables, and pipelines, and how to operate the system at least cost, for the years 2030 and 2040. Within this single model, both networks are represented in two ways, and varied in a controlled comparison. The electricity network is represented either as a simple transport model that moves power subject only to line capacity, or with a DC optimal power flow (DC-OPF) formulation that also enforces the physics of how power flows through the network. The hydrogen network is represented either without linepacking, as a rigid pipeline, or with a four-hour approximation of linepacking, the short-term flexibility of storing gas in the pipelines. Crossing the two gives four scenarios. Every other assumption is held fixed, so any difference in the cost-optimal electrolyser location can be attributed to the representation being tested.

Hydrogen production is onshore-dominated in every scenario and both years, with onshore locations holding more than 80 percent of total electrolyser capacity. Offshore capacity appears only at a few hubs, and the highest offshore share in any scenario is 18.3 percent. Between the two representations, the electricity choice is the decisive one. Moving from the transport model to DC-OPF shifts capacity toward the offshore hubs and the cheaper northern nodes, brings some investment forward into 2030, and raises the total capacity by about 15 percent. The reason is that DC-OPF produces a locational price signal the transport model does not: the flow physics keep cheap northern and offshore power from reaching interior demand, so more expensive producers set the price there, prices separate by location, and electrolyser investment follows the cheaper nodes. The hydrogen representation does not move the onshore-offshore distribution. Linepacking concentrates production in the cheapest hours within the day, but the offshore share and the long-run siting stay close to the base case, because the hydrogen backbone stays uncongested and its prices are almost uniform. The direction of these findings is robust. The exact offshore share is not, because it is conditional on the size of the fixed onshore network and on the cost premium of offshore over onshore production.

The answer to where hydrogen should be produced therefore cannot be separated from how the electricity network is modelled. The location outcome depends not only on the system itself but also on how the model represents it: a representation that admits locational price differences places more electrolyzers offshore, and one that suppresses them places almost all onshore. For modellers, the electricity grid representation is a deliberate choice and not a neutral technical detail. In a model that asks where hydrogen should be produced, it should be selected and reported as carefully as the cost and demand

assumptions. For decision-makers, the results support onshore-dominated hydrogen production as the cost-optimal default, sited at the cheaper northern and coastal nodes where offshore wind reaches land, with offshore production as a targeted addition at specific hubs where delivering wind to shore is constrained. These results should be read for direction rather than as a forecast, since they come from a model that optimises for system cost alone.

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Nomenclature

Abbreviations

Abbreviation	Definition
CCGT	Combined-Cycle Gas Turbine
DC-OPF	Direct Current Optimal Power Flow
EHB	European Hydrogen Backbone
ENTSO-E	European Network of Transmission System Operators for Electricity
ESOM	Energy System Optimisation Model
H ₂ -CCGT	Hydrogen Combined-Cycle Gas Turbine
HVAC	High-Voltage Alternating Current
HVDC	High-Voltage Direct Current
LP	Linear Programming
MILP	Mixed-Integer Linear Programming
NSEC	North Seas Energy Cooperation
NSOG	North Sea Offshore Grid
NSWPH	North Sea Wind Power Hub
NTC	Net Transfer Capacity
OWF	Offshore Wind Farm
PHS	Pumped Hydro Storage
PTDF	Power Transfer Distribution Factor
TYNDP	Ten-Year Network Development Plan

Symbols

Symbol	Definition	Unit
Sets and Indices		
A	Set of all assets, indexed by a	[-]
A^c	Subset of consumer assets (e.g., demand, gridn)	[-]
A^{cv}	Subset of conversion assets (e.g., electrolyzers)	[-]
A^{el}	Subset of electrolyser assets	[-]
A^{inv}	Subset of investable assets	[-]
A^{ow}	Subset of offshore wind assets	[-]
A^p	Subset of producer assets	[-]
A^{ramp}	Subset of assets with ramping constraints	[-]
A^s	Subset of storage assets	[-]
A^{ss}	Subset of seasonal storage assets	[-]
F	Set of all flows, indexed by f	[-]
F^{dc-opf}	Subset of AC electricity lines with DC-OPF constraints	[-]
F^{in}	Subset of incoming flows to a given asset	[-]
F^{inv}	Subset of investable transport flows	[-]
F^{op}	Subset of flows from assets with operational costs	[-]
F^{out}	Subset of outgoing flows from a given asset	[-]
F^t	Subset of transport flows	[-]
K	Set of representative periods, indexed by k	[-]

Symbol	Definition	Unit
P	Set of all actual periods in the timeframe, indexed by p	[-]
p_y^{first}	First actual period in the timeframe	[-]
p_y^{last}	Last actual period in the timeframe	[-]
T	Set of timesteps within a representative period, indexed by t_k	[-]
t_k^{first}	First timestep of a representative period	[-]
t_k^{last}	Last timestep of a representative period	[-]
Y	Set of milestone years, indexed by y	[-]
y^{last}	Final milestone year in the modelled horizon	[-]
Parameters		
$p^{\text{ann inv cost}}$	Annualised investment cost	[EUR/MW/yr]
$p^{\text{availability profile}}$	Normalized availability profile of an energy source	[p.u.]
p^{base}	Power system base	[MVA]
$p^{\text{cap new}}$	Stage 1 capacity (expanded network)	[MW]
$p^{\text{cap orig}}$	Original capacity from the initial network	[MW]
$p^{\text{demand profile}}$	Normalized demand profile	[p.u.]
$p^{\text{disc inv}}$	Annualisation factor for investment costs	[-]
$p^{\text{disc op}}$	Discounting factor for operational costs	[-]
$p^{\text{disc year}}$	Reference year for present value discounting	[yr]
p^{dur}	Duration of a timestep block	[h]
$p^{\text{econ lt}}$	Economic lifetime of an asset or flow	[yr]
p^{eff}	Efficiency of a conversion asset	[p.u.]
$p^{\text{eff in}}$	Charging efficiency of a storage asset	[p.u.]
$p^{\text{eff out}}$	Discharging efficiency of a storage asset	[p.u.]
$p^{\text{fix cost}}$	Fixed annual operating cost	[EUR/MW/yr]
$p^{\text{inv cost}}$	Investment cost	[EUR/MW]
p^{map}	Mapping weight linking a representative to actual period	[-]
$p^{\text{op cost}}$	Operational cost proportional to energy dispatched	[EUR/MWh]
$p^{\text{peak demand}}$	Peak demand for a consumer asset	[MW]
$p^{\text{ramp down}}$	Maximum ramping rate down as a fraction of capacity	[p.u./h]
$p^{\text{ramp up}}$	Maximum ramping rate up as a fraction of capacity	[p.u./h]
$p^{\text{reactance new}}$	Recalculated reactance for the expanded network	[p.u.]
$p^{\text{reactance orig}}$	Original reactance from the initial network	[p.u.]
$p^{\text{reactance}}$	Reactance of a transmission line, normalized	[p.u.]
$p^{\text{rp weight}}$	Weight reflecting periods represented by the timeframe	[-]
p^{salvage}	Salvage value of an asset or flow	[EUR/MW]
$p^{\text{soc dr}}$	Social discount rate	[-]
$p^{\text{tech dr}}$	Technology-specific discount rate	[-]
Continuous Variables		
$C_{\text{assets}}^{\text{fix}}$	Annual fixed operating cost applied to all available asset capacity	[EUR]
$C_{\text{flows}}^{\text{fix}}$	Annual fixed cost for existing and invested transport capacity	[EUR]
$C_{\text{assets}}^{\text{inv}}$	Annualised cost of investing in new asset capacity	[EUR]
$C_{\text{flows}}^{\text{inv}}$	Annualised cost of investing in new transport flow capacity	[EUR]
C^{inv}	Undiscounted direct capital investment cost	[EUR]
$C_{\text{flows}}^{\text{op}}$	Variable operational cost proportional to energy flows	[EUR]

Symbol	Definition	Unit
v^{angle}	Voltage phase angle at a node	[rad]
$v^{\text{available cap}}$	Total available capacity (initial plus investments)	[MW]
v^{flow}	Energy flowing on a connection	[MW]
v^{inv}	Invested continuous capacity for assets or flows	[MW]
v^{storage}	Stored energy level within a representative period	[MWh]
$v^{\text{storage,ip}}$	Inter-period storage level across chronological periods	[MWh]
Derived Metrics		
λ^{cbc}	Raw dual value of the consumer balance constraint	[EUR/MW]
λ^{line}	Marginal reduction in system cost from one unit of line capacity	[EUR/MWh]
$\lambda^{\text{nodal price}}$	Hourly nodal price (corrected locational marginal cost)	[EUR/MWh]
$\bar{\lambda}^{\text{nodal price}}$	Yearly average nodal price	[EUR/MWh]
λ^{tflc}	Raw dual value of the transport flow limit constraint	[EUR/MW]
ϕ	Electrolyser capacity factor	[-]
E^{curt}	Offshore wind curtailment fraction	[-]
U^{flow}	Line utilisation	[-]
C^{disp}	Undiscounted annual dispatch cost	[EUR]

Introduction

1.1. The European energy transition

The European energy system is undergoing a rapid transformation to mitigate the consequences of climate change and establish a sustainable, zero-carbon future. The foundation of the European energy transition is the European Green Deal, which establishes the formal objective of achieving a climate-neutral economy by 2050 (European Commission [EC], 2019). To realise this ambition, a fast and large-scale deployment of renewable energy is required. In particular offshore wind energy is identified as an important pillar of this future energy mix, with the European Commission targeting a major increase in installed capacity by 2050 (EC, 2020). Beyond the necessity of meeting long-term climate targets, recent geopolitical developments have added significant urgency to this transition. The REPowerEU plan emphasises that accelerating the rollout of offshore renewables is critical for enhancing European energy security and rapidly reducing the continent's dependence on imported fossil fuels (EC, 2022).

Driven by these climate and economic objectives, the North Sea has emerged as a central focus for this expansion. In the Ostend Declaration, European energy ministers describe it as Europe's future green power plant and set ambitious deployment targets, aiming for around 120 GW of offshore wind in the North Seas by 2030. Looking further ahead, the European Union, Norway and the United Kingdom plan on integrating more than 300 GW of offshore renewable energy generation capacity by 2050 (Energy Ministers of the North Seas Countries, 2023). By this time, offshore wind is projected to provide 18% of the total dispatched energy in the European power system (European Network of Transmission System Operators for Electricity [ENTSO-E], 2024).

However, the rapid deployment of offshore wind introduces significant system integration challenges. Realising these targets requires a massive expansion of transmission infrastructure. To connect the planned offshore wind farms (OWFs), between 48,000 and 54,000 kilometres of offshore infrastructure installations are needed across Europe (ENTSO-E, 2024). Because wind power is highly intermittent and frequently misaligned with electricity demand, integration into the onshore energy system is difficult. As the installed capacity of offshore wind scales up, national onshore electricity grids face severe bottlenecks and congestion risks, potentially leading to the curtailment of renewable generation. The challenge lies not only in generating the electricity but in ensuring it can be efficiently integrated into Europe's energy systems. Electricity grids are already under pressure, and expanding them requires significant time and capital. The choices that are made now are important for future socio-economic welfare. While initial investments reach hundreds of billions of euros, every euro invested now will save two euros in system costs in 2040 (ENTSO-E, 2025). The countries aim to deliver network infrastructure in time to avoid stranded assets in offshore wind production (Energy Ministers of the North Seas Countries, 2023). Furthermore, recent energy disruptions with enormous price spikes as a consequence highlight the importance of energy security. With a robust integration of the renewably produced offshore energy and a strong interconnection between countries to trade energy, the risk of shortages is reduced. This enhanced energy security also ensures that prices remain stable and affordable for European citizens (ENTSO-E, 2024).

1.2. Hydrogen in the North Sea energy system

To reduce grid congestion and enhance system flexibility, the integration of additional energy carriers such as hydrogen has emerged as a crucial strategy. Hydrogen production via electrolysis adds a flexible electricity demand that can absorb offshore wind generation and ease pressure on the grid (North Sea Wind Power Hub [NSWPH], 2024). The produced hydrogen can serve as long-term energy storage and later be reconverted into electricity via fuel cells or combustion plants. Furthermore, hydrogen can be used as a fuel, reducing emissions in sectors that are difficult to decarbonise, such as industry, transport, and shipping (International Energy Agency [IEA], 2025).

To facilitate this massive integration, initiatives like the North Sea Wind Power Hub are exploring large-scale offshore energy hubs. These hubs combine offshore wind deployment with strong energy exchange infrastructure, including cross-border electricity grids, hydrogen pipelines, and offshore hydrogen production facilities (NSWPH, 2024). Transporting energy as hydrogen via pipelines can be more cost-effective over long distances than high-voltage electrical transmission (Bødal et al., 2024). Additionally, hydrogen transportation also offers inherent flexibility through pipeline storage capacity, called linepacking (Sargent & Sargent, 2025). The EU aims to install 40 GW of renewable hydrogen electrolyzers by 2030, producing about 10 million tonnes of green hydrogen annually (EC, n.d.).

Where to produce this hydrogen is a central design question, because the production location determines which transmission infrastructure must be built. Producing offshore favours hydrogen pipelines and can reduce the need for new and expensive electricity cables. Producing onshore requires bringing the electricity to land first, but keeps electrolyzers easier to operate and maintain (Travaglini et al., 2025). These are large investments, and the choice shapes the North Sea system for many future years. To support these decisions, researchers use energy system models to find the cost-optimal production location. How these models represent the physical system shapes the location they identify as cheapest. Studies differ in how much physical detail they use to represent the electricity grid, and in whether they capture the short-term flexibility of the hydrogen network. As the next section shows, these differences help explain why the literature does not agree on where hydrogen should be produced.

1.3. Knowledge gap

That disagreement is the starting point for this thesis. Studies of the North Sea energy system reach opposite conclusions on where hydrogen should be produced. Some system-level studies find onshore production cheapest (Gea-Bermúdez et al., 2023), others find offshore cheapest (Glaum et al., 2024), and single-farm studies are split in the same way (Jang et al., 2022; McDonagh et al., 2020). The disagreement is not random, but patterned. Which conclusion a study reaches can be attributed to identifiable choices. These choices could be where the system boundary is drawn, whether the electrolyser can trade electricity with the onshore grid, what techno-economic assumptions are used, and how the electricity grid and hydrogen network are represented. Chapter 2 sets out these drivers in more detail.

These drivers are not all the same kind of choice. For example scope defines the system a study models and the question it asks. A single farm or a whole region, or a model with or without a connection to the onshore grid. Studies that differ on system scope are often answering different questions, so their location conclusions cannot be compared directly. Cost and technology assumptions are different. They are genuine uncertainties about the real world, and a single model can test their influence by varying them in a sensitivity analysis. The representation of the electricity grid and the hydrogen network is another type of modelling choice. It is neither the question nor an uncertain value. It is part of how the model is built, and it decides which physics the model includes: whether power flows obey physical network limits, and whether pipelines can buffer gas over short periods. To isolate the effect, the system must be modelled both with the detailed representation and without it, then run both ways while all other assumptions stay fixed. Yet no study has isolated both the electricity grid and hydrogen network representations together this way, at a spatial resolution fine enough to reveal grid constraints, and with hydrogen production location as the outcome. This is the gap this thesis addresses. The uncertainty these choices create falls on policymakers who must commit to large infrastructure investments that shape the future system.

This makes the representation a modelling choice with consequences, not a neutral technical detail. Süsser et al. (2021) argue that energy models are not objective instruments but are shaped by, and in turn shape, the policymaking process around them. Sterman (2002) makes the sharper point that a model's results are usually more sensitive to its boundary and structural choices than to the values of its parameters. Isolating such a choice, rather than assuming its effect, is therefore worth doing.

1.4. Research questions and approach

This leads to the following research question:

How do electricity grid and hydrogen network representations in an energy system model influence the cost-optimal location and configuration of hydrogen production in the North Sea region?

The hypothesis is that detailed network representations provide a more realistic locational cost of energy, which could plausibly have an influence on the siting decision of onshore or offshore electrolysis. Where a simple representation could price locations similarly and gives no locational reason to build in one place, a detailed one exposes where energy is cheap and is expected to draw hydrogen production toward those locations, plausibly offshore near the wind. The research is structured to test this expectation. To answer the research question systematically, the research is broken down into theoretical context, conceptual modelling, and computational results. The first step is outlining the real-world North Sea energy system. Because the exact layout of this future system is still uncertain, the first sub-question explores how the physical and economic infrastructure might be configured:

1. What are the anticipated techno-economic configurations of the future North Sea energy system?

Once these possible configurations (of components such as cables, pipelines, electrolyzers, storage methods, and market structures) are defined, their physical complexity must be translated into a conceptual model. Defining the right modelling abstractions is an essential prerequisite before any computational work can begin. To build this conceptual foundation, the abstractions of the electricity grid and the hydrogen network are examined in the following sub-questions:

2. What key assumptions and modelling abstractions are applied in energy system models when simulating electricity grids?

3. What key assumptions and modelling abstractions are applied in energy system models when simulating hydrogen infrastructure and its operational flexibility?

With these concepts defined, the conceptual model is transformed into a computational structure using the Julia programming language and the Tulipa Energy Model framework. After verification and validation of the model, the final simulations will be executed to obtain the results. This involves running systematic simulations (scenarios) to generate quantitative data on system performance and costs, and electrolyser locations. The last sub-question focuses on generating these results:

4. What are the cost-optimal locations and system configurations of hydrogen production in the North Sea region given certain electricity grid and hydrogen network representations?

The first three sub-questions are addressed through the literature review and the construction of the methodology and case study, which together establish the system and the modelling abstractions. The fourth is addressed through a quantitative analysis of the model results. Answering these four sub-questions provides all the necessary information to address the main research question. Finally, the results are interpreted to gain insights into the real-world problem. The findings will be related to current literature where the specific influence of the different modelling choices is analysed. These academic insights will then form the basis for discussing possible policy implications and recommendations to derive strategic insights.

To answer these questions, this research uses Energy System Optimisation Modelling (ESOM), a standard method for least-cost, long-term energy system planning. The open-source Tulipa Energy Model (Soares Siqueira et al., 2026) is used to build the system as a cost-minimising linear programming (LP) formulation, with continuous investment and dispatch decisions. The optimisation minimises total system cost across the milestone years 2030 and 2040.

The two representations are studied through a 2×2 scenario design. One axis varies the electricity grid: a simple transport model against a DC optimal power flow (DC-OPF) formulation. The other axis varies the hydrogen network: no linepacking against a four-hour temporal resolution as a pipeline flexibility approximation. Combining the two axes gives four scenarios. All other assumptions are held fixed across them, so any difference in the cost-optimal location of hydrogen production can be attributed to the representation being tested. A sensitivity analysis then tests how robust the results are to the most influential uncertain parameters.

1.5. CoSEM relevance

The North Sea energy transition is a socio-technical problem of the kind the Complex Systems Engineering and Management (CoSEM) programme is concerned with. The technical layer, offshore wind, electrolyzers, cables, and pipelines, cannot be planned in isolation from the actors and institutions around it. The system spans several sovereign states with their own energy strategies, markets, and regulators, and no single actor controls the outcome. Because these actors hold competing interests, there is no single solution that is best for all of them, and any real decision involves trade-offs between them. The investments at stake are large, long-term, and they must be committed now under deep uncertainty about the future system. New infrastructure must also fit networks and policy commitments already in place. These assets and their integrating infrastructure are operational for decades and are hard to decommission once built, so an early siting decision narrows the options that remain open. The choices made now therefore shape the system far into the future. These features, many actors with divergent interests, high stakes under uncertainty, and path dependency, are what make the siting of hydrogen production a system problem rather than a purely technical one.

Within that problem, this thesis takes the engineering and analytical view. It uses a cost-optimisation model to ask where hydrogen production is cheapest to site under different representations of the system. The CoSEM relevance is not only in the subject but in the method itself. Energy system models of this kind are used to inform real infrastructure and policy decisions, yet the answer they give depends on how the modeller chooses to represent the system. A modelling choice is therefore not a neutral technical detail. It shapes the advice that reaches decision makers. Making one such choice visible, and showing how much it moves the cost-optimal outcome, is the contribution of this thesis and the reason the question sits at the intersection of technology, analysis, and decision making that defines the programme.

1.6. Thesis outline

The remainder of this thesis is structured as follows. Chapter 2 reviews the literature on offshore hydrogen production. It sets out the possible system configurations, examines why studies disagree on where to produce hydrogen, and shows that the disagreement is patterned. It begins to answer the sub-questions on how electricity grids and hydrogen networks are represented, and then identifies these representations as the structural choices that no study has isolated. Finally it states the research question that follows.

Chapter 3 presents the modelling approach. It explains the choice of energy system optimisation, introduces the Tulipa Energy Model, and gives the mathematical formulation of the linear program, including the objective function, the decision variables, the constraints most relevant to this study, and defines the metrics used to compare the scenarios. The verification and validation of the model are given in Appendix C. Chapter 4 applies this approach to the North Sea. It defines the study area, describes how the offshore network, the onshore electricity grid, and the hydrogen backbone are built from data, and sets out a two-step optimisation and the four scenarios.

Chapter 5 presents the results. It reports the metrics across the four scenarios for 2030 and 2040 and analyses the mechanism behind the siting outcome. Chapter 6 interprets these results, relates them to the literature, states the limitations of the study, and discusses the implications for infrastructure and policy decisions. Chapter 7 answers the four sub-questions and the main research question. Chapter 8 reflects on the research process, the modelling and interpretation lessons of the work, and where the analytical approach of this thesis meets the wider socio-technical decision it sits within.

2

Literature Review

2.1. The North Sea energy system

Several configurations have been proposed for how large-scale offshore wind power generation might be brought to onshore consumers, and no single configuration has yet emerged as clearly preferable. The central infrastructure question is the transmission method: electricity can be transported directly via high-voltage direct current (HVDC) cables, or converted to hydrogen at or near the generation site and moved to shore via submarine pipelines. These options have distinct cost structures that vary with distance and system context, and neither dominates unconditionally. Studies modelling the North Sea represent this dual-carrier architecture in networks including multiple countries, connecting offshore wind clusters to national systems across the region (Farahmand et al., 2024; Gea-Bermúdez et al., 2023).

The physical topology of how offshore assets connect to shore adds another layer of uncertainty. Wind farms can be linked to onshore points through dedicated radial connections or through shared offshore hubs that aggregate generation from multiple OWFs and dispatch it to several countries. This meshed arrangement can carry both electricity and hydrogen within the same offshore network (Glaum et al., 2024), and spatial analyses show that realistic hub placement is constrained by water depth, shipping lanes, and protected marine areas (Martínez-Gordón et al., 2022). Within this configuration space, four generic siting options for hydrogen electrolysis have been identified. In the centralised onshore configuration (C-ON), electricity is transmitted via HVDC cables to shore and hydrogen is produced at a mainland facility. In the centralised offshore configuration (C-OFF), electrolysis takes place at an offshore hub and the resulting hydrogen is transported to shore through pipelines. This includes both dedicated hydrogen hubs, where all offshore wind electricity is converted to hydrogen, and hybrid configurations, where the hub exports hydrogen via pipelines alongside electricity via cables. A fourth option, decentralised offshore production (D-OFF), places electrolyzers at individual turbines, but this is generally considered impractical at commercial scale due to the loss of economies of scale and operational constraints (Travaglini et al., 2025). These configurations are illustrated in Figure 2.1.

Another dimension concerns market design. Offshore generation can be priced as part of a corresponding national electricity market, referred to as the home bidding zone, or within a dedicated offshore bidding zone, where the local electricity price is determined separately from onshore markets and tends to be lower during periods of high wind output (Nieuwenhout, 2022). Analyses of North Sea offshore market structures show this distinction has significant consequences for system-level welfare and investment in offshore infrastructure (Hardy et al., 2023). Most energy system models take the market structure as given and do not compare bidding-zone configurations. Hardy et al. (2023) and Kenis et al. (2024) are the exceptions, treating market design as the variable they test. The physical topology, the transmission method, and the market arrangements are all still undecided in practice. Together they define a configuration space that the existing literature has approached with different models and assumptions. Section 2.2 examines what conclusions have been found on where hydrogen production is most cost-effective within these possible configurations, and why those conclusions conflict.

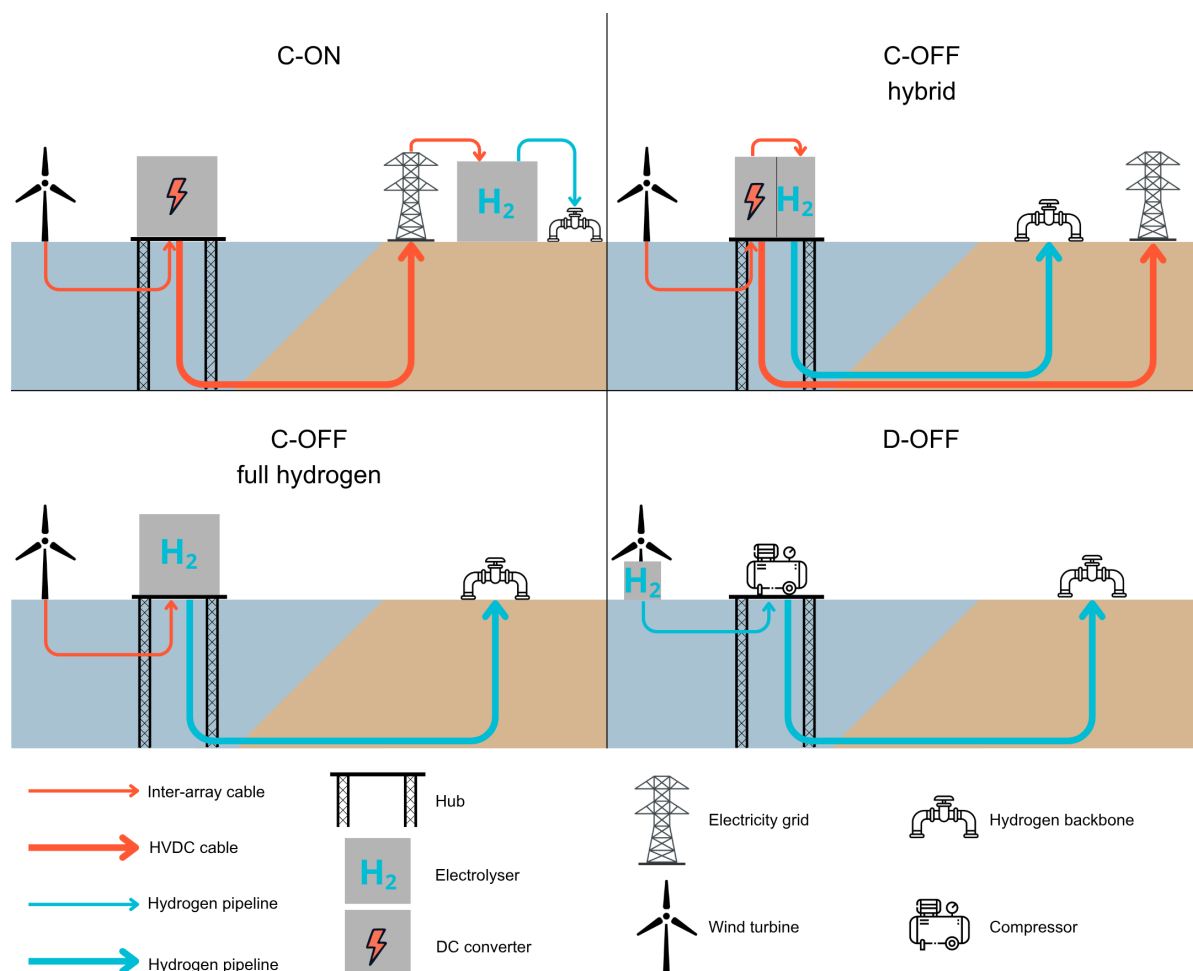


Figure 2.1: Schematic overview of the four hydrogen production siting configurations considered in this study. C-ON: electricity transmitted to shore via HVDC cable, hydrogen produced at an onshore facility. C-OFF (hybrid): offshore hub electrolysis with hydrogen exported via pipeline alongside electricity via HVDC cable. C-OFF (full H₂): offshore hub electrolysis with hydrogen exported via pipeline only. D-OFF: decentralised electrolysis at individual wind turbines, generally considered impractical at commercial scale.

2.2. The hydrogen production location debate

The question of where to produce hydrogen in the North Sea area is not settled in the literature. System-level energy system models reach opposite conclusions: Gea-Bermúdez et al. (2023) find that offshore wind creates significantly more value when transmitted to shore as electricity, making onshore hydrogen production (C-ON) strongly preferable, while Glaum et al. (2024) find that the bulk of offshore wind is most economically transported as hydrogen, favouring centralised offshore production (C-OFF). The disagreement is not only within system-level studies. Single-farm analyses are equally divided: McDonagh et al. (2020) find that if hydrogen is produced, an onshore electrolyser location is preferred for a near-shore wind farm, while Jang et al. (2022) and Travaglini et al. (2025) both conclude that offshore production is preferable for dedicated hydrogen wind farms without grid connections. Although these studies differ in location, scale, and model type, they all ask the same question of where hydrogen is cheapest to produce. Their disagreement therefore reflects the different conditions under which each study asks the question. The disagreement is, however, patterned.

A reliable predictor of which conclusion a study reaches is whether the model allows the wind farm or electrolyser to exchange electricity with the onshore grid at market prices. In these single-farm analyses, C-ON consistently dominates when electricity can be traded with the grid. An onshore electrolyser with grid access can draw cheap electricity from any source, not only from the wind farm. When electricity prices are high, the electrolyser stands down and the wind farm's output is sold to the grid instead. None of these single-farm studies models the onshore grid itself. The electricity price is an exogenous input rather than an outcome of network constraints, and curtailment is set as an assumption rather than derived from congestion on specific lines. The price that influences the siting outcome is therefore input to the model, not produced by it. McDonagh et al. (2020) show one form of this price-driven mechanism through the connection with an onshore grid. They place the electrolyser onshore, where it acts as a price floor: instead of selling the wind farm's electricity at low or negative prices, the operator converts it into hydrogen, with a higher value in that moment. The paper shows that this price-floor effect, not the conversion of electricity that would otherwise be curtailed, is the main source of value. When McDonagh et al. (2020) isolate the wind farm from the grid, the comparison reduces to transmission costs alone: offshore hydrogen production avoids expensive substations and export cables, making pipelines the cheaper option at the distances that are considered. Jang et al. (2022) model a 160 MW farm with no onshore market connection and find C-OFF and D-OFF cheaper than C-ON for exactly this reason. Travaglini et al. (2025) reach the same C-OFF conclusion for a dedicated offshore farm. Calado et al. (2024), by contrast, model a wind farm connected to the Iberian electricity market and find C-ON preferable, though the specific market conditions and floating-wind technology of that case study limit how far the results can be generalised. Travaglini et al. (2025) attribute this difference to the grid electricity purchase available in Calado et al. (2024), which confirms grid electricity trading as a primary driver, alongside physical and geographic differences between sites. This pattern is not a physical contradiction. It is a consequence of where the model draws its system boundary.

Capital cost attribution provides a second, independent driver. Jang et al. (2022) find that when wind turbine capital costs are attributed fully to the hydrogen project (a greenfield development), offshore configurations are preferred because they avoid the cost of electrical export infrastructure. When Jang et al. (2022) instead treat the wind farm as already built and the electrolyser as an add-on, C-ON becomes the cheapest option. The conclusion reverses on this single assumption change. This sensitivity acts independently of the grid connection question and shows how a single assumption can determine the location conclusion.

Among the system-level studies, three modelling differences explain why Gea-Bermúdez et al. (2023) and Glaum et al. (2024) reach opposite conclusions despite studying comparable systems. First, Glaum et al. (2024) assume higher HVDC transmission costs, raising the relative attractiveness of pipeline transport. Second, Glaum et al. (2024) model the offshore system at finer spatial resolution, allowing the optimiser to distinguish locations with different wind resources and transmission requirements rather than treating offshore zones as uniform. Third, Glaum et al. (2024) model hydrogen demand internally in Europe, including industrial use and synthetic fuels, which substantially increases the total volume of hydrogen to be transported and shifts the balance towards bulk pipeline export. Together, these show that even between studies of comparable scope, the results are sensitive to modelling choices that vary across studies.

The C-ON versus C-OFF distinction also covers a range of configurations rather than a binary switch. Löhr et al. (2023) evaluate North Sea offshore infrastructure using a dispatch model and find that while C-OFF reduces capital expenditure by avoiding HVDC cables, it raises operational costs substantially when transmission capacity is insufficient to clear offshore generation, producing congestion and curtailment costs that partly offset the infrastructure savings. C-ON and C-OFF are therefore better understood as points on a trade-off between capital and operational expenditure than as discrete alternatives. Martínez-Gordón et al. (2022) reach a similar conclusion: in their North Sea model, offshore electrolysis acts as a complement to onshore production rather than a replacement, with both configurations playing distinct roles in the cost-optimal system. Distance to shore adds a further dimension: Travaglini et al. (2025) find that offshore hydrogen costs decrease between approximately 50 and 100 kilometres from shore as wind resources improve, then rise beyond that range as pipeline costs dominate. Near-shore studies tend to find C-ON preferable; far-shore studies tend to favour C-OFF. This means comparisons between papers studying sites at different distances are not straightforward, and the same model can shift its conclusion simply by changing the assumed site location.

Bødal et al. (2024) add a further dimension: in their North Sea model, offshore electrolysis is only competitive within a medium electricity price window, with the location outcome determined by the assumed price level and offshore capital costs of the electrolyser. Table 2.1 provides an overview of the reviewed studies with their network representations, primary driver, and conclusion. In the single-farm studies the conclusion follows from grid trading. In the system studies no single driver is decisive, and the primary-driver column identifies what separates each result. The two network columns capture whether the electricity model imposes physical flow constraints (transport versus DC-OPF) and whether the hydrogen model can buffer flow over time (linepacking).

Table 2.1: Reviewed studies on hydrogen production location, showing the network representations and assumptions that drive each conclusion, and the positioning of this study. Electricity and hydrogen network representations are examined in detail in Sections 2.3 and 2.4.

Study	Scope	Electricity network	Grid trading availability	Hydrogen network	Main driver of conclusion	Conclusion
McDonagh et al. (2020)	Single farm	Point-to-point, grid-connected	Yes, exogenous	None (fixed-price sink)	Market prices (Acts as price floor) & freshwater access	C-ON
Calado et al. (2024)	Single farm	Point-to-point, grid-connected	Yes, exogenous	Pipeline, static linepacking	Grid purchase access	C-ON
Jang et al. (2022)	Single farm	Point-to-point, no grid connection	No, isolated	Pipeline, no linepacking	Transmission CAPEX attribution (Avoids HVDC & substations)	C-OFF/D-OFF
Travaglini et al. (2025)	Single farm	Point-to-point, no grid connection	No, isolated	Pipeline, no linepacking	Transmission CAPEX & economies of scale	C-OFF
Gea-Bermúdez et al. (2023)	System ESOM	Network, NTC transport	Yes, endogenous	Network transport, no linepacking	Market prices & onshore synergies	C-ON
Glaum et al. (2024)	System ESOM	Network, transport	Yes, endogenous	Network transport, no linepacking	CAPEX (HVDC platform & cable cost)	C-OFF
Löhr et al. (2023)	System dispatch	Network, DC-OPF onshore	Yes, endogenous	Network transport, no linepacking	Transmission CAPEX against system OPEX	C-ON/C-OFF (trade-off)
Martínez-Gordón et al. (2022)	System ESOM	Network, transport	Yes, endogenous	Network, daily balance (proxy)	Transmission CAPEX & local flexibility	C-ON/C-OFF
Bødal et al. (2024)	System ESOM	Network, transport	Yes, exogenous	Network transport, with linepacking	Market prices & offshore premium	C-ON/C-OFF (threshold)
This study	System ESOM	Network, transport vs. DC-OPF	Yes, endogenous	Network, no linepacking vs. 4h proxy	Isolates network representation; other choices fixed	Research question

Together, the reviewed studies show that much of the C-ON versus C-OFF disagreement can be traced to certain modelling choices. Allowing the electrolyser to trade electricity with the onshore grid favours onshore production. Attributing the full wind farm capital cost to the hydrogen project favours offshore. So do high HVDC cost assumptions, a fine offshore spatial resolution, and a large internal hydrogen demand that must be transported. Some of these differ because the studies differ in scope and ask different questions, which makes their results not directly comparable. Others reflect genuinely different cost assumptions, which sensitivity analysis within a model could address. Another group of choices, however, concerns not what values the model uses but what physical phenomena it can represent: whether the electricity network captures congestion from physical flow constraints, and whether the hydrogen network can buffer supply across time. No existing study has systematically isolated the

effect of either. The following two sections examine them in turn.

2.3. Electricity grid modelling abstractions

Energy system models represent the electricity network at different levels of physical detail. In a simple transport model, power flows between nodes are limited only by transmission capacity, and the model is free to route electricity along any path as long as line limits are not exceeded. In a DC optimal power flow (DC-OPF) representation, flows are additionally constrained by Kirchhoff's voltage law, meaning that power distributes across the network according to line impedances. DC-OPF is itself a linear approximation of the full AC power flow: it drops reactive power and voltage magnitudes, but keeps the loop-flow behaviour that the transport model ignores. The choice between transport and DC-OPF has an influence on the optimal electrolyser location. First, physical flow constraints limit which dispatch patterns are feasible and can require conversion at specific network locations rather than allowing it to shift more freely. Second, binding constraints generate nodal price differences: the shadow price of a constraint becomes the implicit local electricity price. In a cost-minimising linear programming (LP) model, these two causes are mathematically intertwined, because the price at each node is determined by the shadow value of the constraint binding there.

The most direct test comes from Cao et al. (2021), the only reviewed study that compares grid modelling methods within one model. They switch between transport modelling, DC-OPF, and PTDF (power transfer distribution factor) approaches within the same ESOM while holding all other parameters constant. PTDFs express what fraction of a transfer between two nodes physically flows over each line, giving the same flow pattern as DC-OPF without solving for voltage angles. At country-level spatial aggregation across Europe, all three approaches produce nearly identical results, with differences in grid investment of around 5% and differences in all other system indicators below 1%.

Cao et al. (2021) themselves attribute this result to their spatial resolution rather than to the real differences between the approaches. With one node per country, the aggregation is too coarse for any method to detect internal congestion, so the effect does not appear. Löhr et al. (2023) show that DC-OPF applied at a finer resolution produces results that are sensitive to the choice of offshore configuration. Whether a transport model at that same resolution would produce the same results remains untested. Evidence from operational power system studies points to the same mechanism: Aravena et al. (2021) show more broadly that suppressing locational price information through spatial aggregation reduces operational efficiency. By comparing current European zonal market designs with a fully nodal pricing model in a Central Western European setting, they demonstrate an operational cost reduction of approximately 5%. Although this is an operational result rather than a long-term investment finding, it clearly indicates the physical network information that is lost with spatial aggregation.

Grid representation influences electrolyser location primarily through the price signals it generates at each node. As electricity is the dominant input cost in hydrogen production, a lower offshore electricity price reduces production costs directly and can offset the higher capital costs of installing an electrolyser offshore. Kenis et al. (2024) illustrate this mechanism: nodal offshore pricing produces lower electricity prices at offshore nodes than zonal configurations. When the cable between an offshore node and the onshore grid is congested, local offshore wind supply exceeds what can be exported, and the offshore node price falls below the onshore price. Nodal pricing captures this. Under a zonal design the offshore price is tied to the onshore zone price and the difference does not appear. This lower offshore price improves electrolyser economics and raises offshore electrolyser investment. Under zonal pricing the incentive falls, because the offshore price is replaced by the onshore zonal price. Transmission limits operate alongside these price signals. Lüth et al. (2024) show that reducing offshore interconnector capacity raises offshore electrolyser utilisation, because congestion forces more electricity to be converted locally rather than exported. The grid representation therefore influences location decisions through both channels: the price signals it generates at each node and the physical capacity limits it imposes on dispatch.

The mainstream approach in North Sea energy system models is simple transport or net transfer capacity (NTC) based flow, which limits exchange between regions by a single capacity value without representing the physics within them (Farahmand et al., 2024; Gea-Bermúdez et al., 2023; Glaum et al., 2024; Martínez-Gordón et al., 2022). Löhr et al. (2023) is the only North Sea study to apply DC-OPF

to the onshore AC grid. No North Sea ESOM has run the controlled within-model comparison that Cao et al. (2021) conducted at European scale, and no such comparison has used electrolyser location as its primary outcome variable. The finding from Cao et al. (2021) shows that this comparison only becomes relevant above a certain spatial resolution threshold.

2.4. Hydrogen network modelling abstractions

Just as electricity networks can be represented with more or less physical detail, so can hydrogen networks. In hydrogen pipelines, the relevant physics concern how pressure and flow vary along the pipe as supply and demand conditions change. Simple pipeline models treat the network as a fixed-capacity transport link and ignore these dynamics. A more physically detailed representation accounts for the fact that when supply exceeds demand, pressure rises and the pipeline holds additional gas, and when demand exceeds supply, pressure falls and the stored gas is released. This is linepacking: the use of pipeline pressure variations as a form of short-term storage. Sargent and Sargent (2025) confirm that hydrogen pipelines can provide this flexibility, though at a lower level than equivalent natural gas pipelines. The question is therefore whether energy system models capture it.

Most do not. The mainstream approach treats hydrogen pipelines as rigid point-to-point links that move gas between nodes with no storage capability. Gea-Bermúdez et al. (2023), Glaum et al. (2024), and Löhr et al. (2023) all model pipelines this way. Omitting linepacking is therefore the norm rather than the exception.

One North Sea study forms the exception. Bødal et al. (2024) is the only North Sea energy system model in the reviewed literature that includes pipeline linepacking explicitly. Its storage resets at the boundary of each representative period, so it captures the short-term flexibility that linepacking provides but does not extend it across longer timescales. Including linepacking changes the electrolyser investment results. It brings the timing of offshore electrolyser deployment forward, shifting it into 2030 rather than 2040, and makes investment more robust against electricity price variation. Its dominant effect, however, is a large increase in onshore electrolysis, and peak offshore electrolyser capacity is lower with linepacking than without it. The location outcome in the first place is driven primarily by the assumed electricity price level and the offshore capital cost premium, not by pipeline flexibility. Martínez-Gordón et al. (2022) take a coarser approach, using a daily hydrogen balance as an approximation for pipeline storage. This is a method of representing linepacking indirectly in a North Sea model, though the authors adopt it to represent the buffering capacity of gas pipelines rather than to isolate the effect of linepacking on electrolyser location. Calado et al. (2024) include pipeline storage in a different way again, using the gas held inside the pipeline to size an external storage tank, in a single-farm setting rather than across a network.

These representations in energy system models simplify a physical reality that is non-linear. Two engineering studies show what a fuller representation involves. Jottrand and Hendrick (2025) model hydrogen pipeline flow as a sequence of steady states, solving the flow as if it were momentarily stable at each step, and still acknowledge that this cannot capture sudden peaks. Ameli et al. (2025) use a full non-linear formulation to show what a complete physical representation requires, and find that integrating more renewable generation raises the linepacking flexibility a system needs. If even a detailed engineering model cannot capture all the physics, the simpler representations in energy system models are approximations too. This does not make them invalid, but their results indicate the direction and scale of the linepacking effect rather than exact values.

Two conclusions follow for the state of the literature. Only one North Sea energy system model includes linepacking, and while that study does compare results with and without it, it does not isolate linepacking as a controlled part of the analysis. No study has systematically investigated how linepacking changes the cost-optimal location of hydrogen production as an isolated modelling choice. Bødal et al. (2024) themselves point to the broader gap, citing Klatzer et al. (2022) to identify linepacking in hydrogen energy system models as a recognised research gap. The effect of representing short-term hydrogen storage on electrolyser location therefore remains underexplored.

2.5. Synthesis and knowledge gap

The preceding sections show that the onshore versus offshore electrolysis disagreement in the literature is not the result of studies finding genuinely different answers to the same question. It is the result of studies asking the question under different conditions: different system boundaries, cost assumptions, spatial resolutions, and representations of physical infrastructure. Some of these differences come from studies asking the question under a different scope, which makes their results not directly comparable. Others reflect genuine uncertainty about real-world parameters, which sensitivity analysis could address. The representation of physical infrastructure is different from both: it is not a value but a structural feature of the model. Section 2.3 showed that the representation of the electricity grid, specifically whether physical flow constraints are modelled or ignored, is capable of changing where congestion appears and what price signals electrolyzers face. Section 2.4 showed that the representation of the hydrogen network, specifically whether pipeline pressure dynamics are captured, is capable of changing which electrolyser investments are more viable. Neither effect has been isolated in a controlled study that holds all other parameters constant.

The closest existing controlled comparison for the electricity grid side is Cao et al. (2021), who systematically tested transport modelling, DC-OPF, and PTDF approaches within the same model. That study found negligible differences, but the authors themselves attribute this to spatial resolution: with one node per country, no flow method can detect internal congestion. Three features distinguish this thesis from that research. First, the geographic scope is the countries surrounding the North Sea rather than the whole European continent. Second, the spatial resolution is at NUTS-2 level, which is finer than the country-level aggregation where Cao et al. (2021) found the effect to disappear. Third, the primary outcome variable is the cost-optimal location of hydrogen electrolysis rather than transmission investment or generation mix. No existing study combines all three features.

For the hydrogen network side, Bødal et al. (2024) remains the only North Sea energy system model to include linepacking explicitly, and they compare results with and without it. However, isolating the effect of linepacking on electrolyser location is not a controlled part of its analysis, and they use an exogenous electricity price rather than one determined endogenously by grid representation. No other study has addressed this directly, and Bødal et al. (2024) acknowledge this gap, citing Klatzer et al. (2022) who identify hydrogen linepacking modelling in energy systems as an open research area.

This research addresses both gaps through a two-by-two scenario design. The electricity grid representation is varied between simple transport and DC-OPF, and the hydrogen network representation is varied between no linepacking and a temporal-resolution approximation for pipeline flexibility, while all other model parameters are held constant. Table 2.2 positions existing North Sea studies within this design space. The outcome variable in each scenario is the cost-optimal location and configuration of hydrogen production in the North Sea region. By varying only the two structural representations while keeping everything else fixed, the design isolates their individual and combined effects, which no existing North Sea study has done. This leads to the following research question:

How do electricity grid and hydrogen network representations in an energy system model influence the cost-optimal location and configuration of hydrogen production in the North Sea region?

Table 2.2: Two-by-two scenario design of this study, positioning representative North Sea energy system models within the design space. The DC-OPF and linepacking combination has not previously been studied at North Sea resolution with electrolyser location as the primary outcome variable.

		Electricity grid representation	
		Simple transport	DC-OPF
Hydrogen network representation	No linepacking	Gea-Bermúdez et al. (2023) Glaum et al. (2024) Farahmand et al. (2024) Martínez-Gordón et al. (2022)	Löhr et al. (2023)
	Linepacking	Bødal et al. (2024)	No existing study

Research Methodology

3.1. Research approach

To address the main research question a modelling approach is selected as the primary research strategy. Because the research question explicitly investigates the impact of modelling choices, this modelling approach is not just the tool but also the object of study. This study will specifically use Energy System Optimisation Modelling (ESOM). Plazas-Niño et al. (2022) identify this as the standard methodology for long-term energy planning, as it enables the determination of a least-cost energy mix under complex constraints such as demand, emissions targets, and technological limits.

An explorative approach is needed to simulate future scenarios as empirical evaluation is impossible for a yet unrealised North Sea offshore grid. This aligns with the "exploratory" function of modelling described by Epstein (2008), where the objective extends beyond precise prediction. Instead, the value lies in illuminating core dynamics and uncovering underlying trade-offs. By systematically adjusting electricity grid and hydrogen network representations, the model isolates their influence on the cost-optimal location of hydrogen production, directly addressing the conflicting findings highlighted in Chapter 2.

The core problem is formulated using Linear Programming (LP), which is suitable for optimizing continuous variables such as electricity dispatch and investment capacities. The optimisation simultaneously determines investment decisions and operational decisions.

On the operational side, the model decides at every timestep which producers to activate. Cheaper producers are dispatched first, consistent with the merit order principle that governs real electricity markets. Both electricity and hydrogen demand must be met at every node at every timestep. Electrolysers convert electricity to hydrogen to meet demand and can be placed at multiple locations. The model invests in electrolysers where investment costs and electricity are cheapest, as this directly determines the cost of hydrogen production. Storage and other conversion assets provide additional flexibility, enabling cheaper ways to balance supply and demand across time and between energy carriers.

All investment and dispatch variables are treated as continuous, keeping the model as a pure LP formulation. This keeps the optimisation computationally tractable across the full multi-year problem. This is acceptable given that individual unit-level decisions are not the focus of this study, and therefore unit commitment constraints will not be activated.

To implement this, the open-source Tulipa Energy Model framework will be used, developed by TNO (Soares Siqueira et al., 2026). The research approach is operationalized through a 2×2 scenario design, systematically comparing electricity grid and hydrogen network representations across four model configurations. One axis of comparison is the electricity grid representation, comparing a simple transport model versus DC optimal power flow. The other axis is the hydrogen network representation, comparing the network without versus with linepacking flexibility. The scenario design is executed in two steps. A preparatory optimisation first determines cost-optimal network capacities for each milestone year using the transport flow formulation with investable electricity and hydrogen grids. These

capacities are then fixed as the common infrastructure basis for all four scenario runs, ensuring that differences in results can be attributed to network representation rather than differences in underlying infrastructure. The specific implementation and expected effects of each representation are defined in detail in Section 4.5.

3.2. Tulipa Energy Model

The Tulipa Energy Model (Soares Siqueira et al., 2026) is an open-source energy system optimisation framework developed by TNO and implemented in the Julia programming language. It was selected as the modelling framework for this research for several reasons that directly align with the requirements of the study, as confirmed by an independent evaluation of 14 open-source integrated planning models (Electric Power Research Institute [EPRI], 2025).

Centrally, Tulipa is a multi-carrier model that simultaneously optimises flows across different energy carriers within a single integrated optimisation problem, which in this study captures the interactions between the electricity and hydrogen systems. This is essential for answering the research question, as the cost-optimal location of hydrogen production is determined by the interaction between electricity grid constraints and hydrogen network structure, and these two systems cannot be meaningfully studied in isolation.

The model represents an energy system as a directed graph of assets and flows, where assets capture physical components such as generators, demand points, storage, and conversion units, and flows capture the connections between them across any energy carrier. This allows the North Sea electricity grid and hydrogen backbone to be represented together within a single spatial network, with offshore hub nodes and onshore regional nodes connected through both electricity transmission flows and hydrogen pipeline flows. Figure 3.1 illustrates this structure of the different connected asset types for the North Sea system. The electricity and hydrogen grid nodes are modelled as consumer assets with zero peak demand, acting as balancing hubs that enforce energy conservation at each node without representing actual consumption.

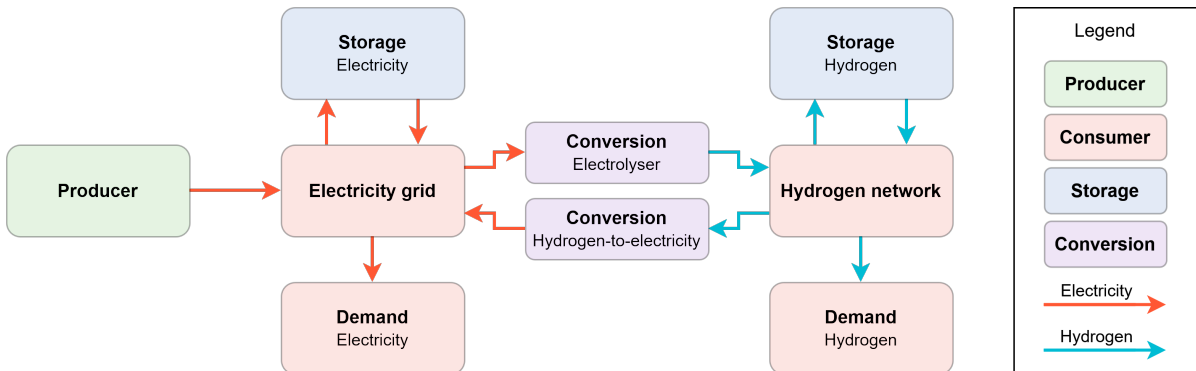


Figure 3.1: Asset types and energy flows in the Tulipa Energy Model.

For the electricity grid, Tulipa supports both a simple transport flow formulation and a Direct Current Optimal Power Flow (DC-OPF) formulation, making it possible to implement the two electricity grid representations examined in this study within the same model framework, as discussed in Section 4.5.3. Furthermore, Tulipa's fully flexible temporal resolution allows different assets and flows to operate at different timestep lengths simultaneously. This enables the simulation of hydrogen linepacking by assigning multi-hour timestep blocks to hydrogen pipeline flows, as discussed in Section 4.5.4. These two features together make Tulipa highly suited to the 2×2 scenario design at the core of this research. EPRI (2025) notes that Tulipa is among a small group of emerging frameworks that combine multi-energy sector coupling with detailed physical network representation, including DC-OPF, within a single model.

Finally, Tulipa supports multi-year investment pathways with milestone years, allowing capacity expansion decisions to be optimised across the 2030 and 2040 horizon of this study. For computational purposes, Tulipa also supports clustering of time series into representative periods, which reduces model

size while preserving key temporal dynamics. The open-source nature of the framework ensures full transparency and reproducibility of the model setup.

The following subsection describes the mathematical formulation of the model, focusing on the objective function and the constraints most relevant to this research.

3.3. Mathematical formulation

The Tulipa Energy model contains four types of assets (the nodes in the graph): producers $a \in A^p$ (e.g., offshore wind turbines), consumers $a \in A^c$ (e.g., electricity or hydrogen demand), storage $a \in A^s$ (e.g., batteries, pumped hydro), and conversion assets $a \in A^{cv}$ (e.g., electrolyzers, hydrogen turbines). A consumer asset with zero demand acts as a balancing hub, enforcing energy balance at a node without representing actual consumption. Flows represent the connections between assets, such as transmission lines or pipelines, and can be unidirectional or bidirectional transport flows. The model guarantees an energy balance at every asset for every timestep within each representative period, while respecting the physical limits on all flows.

The model operates over a timeframe, which is divided into representative periods, each consisting of consecutive timesteps. A key feature of Tulipa is its fully flexible temporal resolution: each asset and flow can be assigned its own timestep length independently of others. For example, electricity assets can be modelled at hourly resolution while hydrogen assets operate at four-hour blocks, maintaining the dynamics relevant to each energy carrier. The resolution of a balance constraint at any asset is determined automatically as the highest resolution among all flows connected to that asset, ensuring physical consistency across sectors with different temporal resolutions (Gao et al., 2025).

Tulipa offers several methods for representing multi-year investments. This study uses the simple investment method, in which all available capacity at each milestone year is aggregated regardless of when it was commissioned, so the model does not distinguish between vintages within a milestone year (Wang & Morales-España, 2025). Consequently, cost and profile assumptions are defined per milestone year rather than per commission year. For each milestone year, the model optimises both investment decisions and the hourly operation of the system, subject to the formulas described below. Throughout the formulation, p denotes fixed input parameters and v denotes decision variables optimised by the solver. The equations in this section and in Appendix A are written for the model configuration used in this study, with the indices and notation adapted accordingly. They therefore state the terms that are active here, and leave out the parts of the Tulipa formulation that this configuration does not use, such as unit commitment, vintage tracking, stochastic scenarios, storage losses over time, and storage inflows. The model uses a deterministic formulation with perfect foresight: all future costs, demand levels, and technology parameters are assumed known at the time of optimisation. While Tulipa supports stochastic formulations with probability-weighted scenarios, this study uses a single deterministic optimisation per scenario run, as the variation of interest is between representations, not between stochastic futures.

3.3.1. Objective function

The model minimises total discounted system cost across all milestone years, and consists of three cost types for flows and assets: annualised investment costs for new capacity, fixed annual operating costs for existing and invested capacity, and variable operational costs proportional to energy flows. The objective function takes the form:

$$\text{minimize } C_{\text{assets}}^{\text{inv}} + C_{\text{assets}}^{\text{fix}} + C_{\text{flows}}^{\text{inv}} + C_{\text{flows}}^{\text{fix}} + C_{\text{flows}}^{\text{op}} \quad (3.1)$$

where each term is defined in the equations found below. Y denotes the set of milestone years, A the set of all assets, F the set of all flows, K the set of representative periods, and T_k the set of the timesteps within representative period k . Each representative period is assigned a weight $p_k^{\text{rp weight}}$ reflecting how many periods of the full timeframe it represents.

Asset investment cost is the annualised cost of investing in new asset capacity across all investable assets A_y^{inv} and milestone years:

$$C_{\text{assets}}^{\text{inv}} = \sum_{y \in Y} \sum_{a \in A_y^{\text{inv}}} p_{a,y}^{\text{disc inv}} \cdot p_{a,y}^{\text{inv cost}} \cdot v_{a,y}^{\text{inv}} \quad (3.2)$$

where $p_{a,y}^{\text{disc inv}}$ is the annualisation factor that converts the investment cost into an equivalent annual cost accounting for the economic lifetime and discount rate. The corresponding formula is found in Appendix A.1. The parameter $p_{a,y}^{\text{inv cost}}$ is the investment cost in EUR/MW and $v_{a,y}^{\text{inv}}$ is the continuous investment capacity variable in MW.

Asset fixed cost is the annual fixed operating cost applied to all available capacity, whether existing or newly invested:

$$C_{\text{assets}}^{\text{fix}} = \sum_{y \in Y} \sum_{a \in A_y} p_y^{\text{disc op}} \cdot p_{a,y}^{\text{fix cost}} \cdot v_{a,y}^{\text{available cap}} \quad (3.3)$$

where $p_y^{\text{disc op}}$ is the discounting factor for operational costs, also found in Appendix A.1. The parameter $p_{a,y}^{\text{fix cost}}$ is the fixed cost in EUR/MW/year. The variable $v_{a,y}^{\text{available cap}}$ is the total available capacity in MW, combining initial units and any new investments.

Flow investment cost is the annualised cost of investing in new transport flow capacity, applicable to investable electricity lines and hydrogen pipelines F_y^{inv} :

$$C_{\text{flows}}^{\text{inv}} = \sum_{y \in Y} \sum_{f \in F_y^{\text{inv}}} p_{f,y}^{\text{disc inv}} \cdot p_{f,y}^{\text{inv cost}} \cdot v_{f,y}^{\text{inv}} \quad (3.4)$$

where the parameters for flows f are applied analogously as to assets a .

Flow fixed cost is the annual fixed cost for existing and invested transport capacity. The factor $\frac{1}{2}$ corrects for the bidirectional nature of transport flows, which would otherwise be counted twice:

$$C_{\text{flows}}^{\text{fix}} = \frac{1}{2} \sum_{y \in Y} \sum_{f \in F_y} p_y^{\text{disc op}} \cdot p_{f,y}^{\text{fix cost}} \cdot v_{f,y}^{\text{available cap}} \quad (3.5)$$

where $v_{f,y}^{\text{available cap}}$ includes both export and import capacity since transport flows are bidirectional.

Flow operational cost is the variable cost proportional to energy dispatched through each flow, summed across all milestone years and timesteps:

$$C_{\text{flows}}^{\text{op}} = \sum_{y \in Y} \sum_{f \in F_y} \sum_{k \in K} \sum_{t_k \in T_k} p_y^{\text{disc op}} \cdot p_k^{\text{rp weight}} \cdot p_{t_k}^{\text{dur}} \cdot p_{f,y}^{\text{op cost}} \cdot v_{f,k,t_k}^{\text{flow}} \quad (3.6)$$

where $p_{f,y}^{\text{op cost}}$ is the operational cost in EUR/MWh and $v_{f,k,t_k}^{\text{flow}}$ is the energy flow in MW. The parameter $p_k^{\text{rp weight}}$ is the weight of the representative period k , reflecting how many periods of the full timeframe it represents, and $p_{t_k}^{\text{dur}}$ is the duration of timestep block t_k .

3.3.2. Decision variables

Parameters p are (based on) fixed input values, but the solver is free to choose values for the decision variables v within the boundaries imposed by the constraints. The solver simultaneously determines the optimal values of all decision variables to minimise total system cost. In Tulipa, all physical quantities in the energy system are represented as flows between assets, with which all asset in- and output can be captured with a single variable type.

The decision variables in this model are listed in Table 3.1. The central operational variable is $v_{f,k,t_k}^{\text{flow}}$: it represents the energy flowing on connection f during timestep t_k of representative period k . Depending on the type of assets it connects, it can simultaneously capture the output of a producer, the activity of a conversion asset, the charge or discharge of a storage asset, and the transmission of energy along the

connection. The two investment variables $v_{a,y}^{\text{inv}}$ and $v_{f,y}^{\text{inv}}$ determine how much new capacity is added for assets and flows at each milestone year, and are treated as continuous variables. The storage level variable $v_{a,k,t_k}^{\text{storage}}$ tracks the state of charge of each storage asset across timesteps and links this between periods through the storage balance constraint.

$v_{a,k,t_k}^{\text{angle}}$ is an auxiliary variable that enforces the DC-OPF power flow physics rather than representing an operational or investment choice. Its value follows implicitly from the network topology, reactances, and flow values. It is only present in the two DC-OPF scenarios.

Table 3.1: Decision variables of the optimisation model, with their units and domains.

Variable	Description	Unit	Domain
$v_{f,k,t_k}^{\text{flow}}$	Flow on connection f during timestep t_k of representative period k	MW	$\mathbb{R}$
$v_{a,y}^{\text{inv}}$	Invested capacity of asset a at milestone year y	MW	$\mathbb{R}_+$
$v_{f,y}^{\text{inv}}$	Invested capacity of transport flow f at milestone year y	MW	$\mathbb{R}_+$
$v_{a,k,t_k}^{\text{storage}}$	Stored energy level of storage asset a during timestep t_k of representative period k	MWh	$\mathbb{R}_+$
$v_{a,k,t_k}^{\text{angle}}$	Voltage phase angle at node a during timestep t_k of representative period k , DC-OPF scenarios only	rad	$\mathbb{R}$

Note that $v_{f,k,t_k}^{\text{flow}}$ has the domain $\mathbb{R}$ because transport flows are bidirectional. A negative value indicates flow in the reverse direction relative to how the connection is defined. Non-transport flows are bounded below by zero through a lower limit constraint.

3.3.3. Constraints

The constraints define the boundaries within which the solver must find the cost-optimal solution. They ensure energy balance at every node, set capacity limits on assets and flows, track storage levels across time, and enforce power flow laws in the DC-OPF scenarios. This subsection describes the constraints that are the most relevant to this research.

The consumer balance constraint enforces energy conservation at every transportation node and demand point at every timestep:

$$\sum_{f \in F_{a,y}^{\text{in}}} v_{f,k,t_k}^{\text{flow}} - \sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k}^{\text{flow}} = p_{a,y}^{\text{peak demand}} \cdot p_{a,k,t_k}^{\text{demand profile}} \quad \forall a \in A^c, y \in Y, k \in K, t_k \in T_k \quad (3.7)$$

where $p_{a,y}^{\text{peak demand}}$ is the peak demand in MW and $p_{a,k,t_k}^{\text{demand profile}}$ is the normalized demand profile in per unit during timestep t_k of representative period k for the set of all consumer assets A^c . For demand nodes their product gives the required consumption at each timestep. Transportation nodes have no demand and serve as balancing points. The inflow and outflow must be exactly equal to each other.

The asset capacity constraint limits the total power delivered across all outgoing flows of an asset at any timestep, ensuring it does not exceed the available installed capacity scaled by the availability profile:

$$\sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k}^{\text{flow}} \leq p_{a,k,t_k}^{\text{availability profile}} \cdot v_{a,y}^{\text{available cap}} \quad \forall a \in A^p \cup A^{\text{cv}} \cup A^s, y \in Y, k \in K, t_k \in T_k \quad (3.8)$$

where $p_{a,k,t_k}^{\text{availability profile}}$ is the normalized availability profile of the energy source in per unit, for intermittent sources a fluctuating time-series. Where no profile is defined for an asset, it defaults to 1, meaning the asset is available at full capacity at all times. The variable $v_{a,y}^{\text{available cap}}$ is the total available capacity in MW as earlier defined at the objective function. This constraint also applies to storage and conversion assets, limiting their discharging and conversion rate to the available capacity. A matching constraint limits the incoming flows of storage assets to the available charging capacity.

The transport flow constraint limits the physical transport capacity of the electricity grid and hydrogen pipelines. Since these transport flows F^t are bidirectional but defined as directed, the flows can be negative but bounded by the same maximum capacity:

$$-v_{f,y}^{\text{available cap}} \leq v_{f,k,t_k}^{\text{flow}} \leq v_{f,y}^{\text{available cap}} \quad \forall f \in F^t, y \in Y, k \in K, t_k \in T_k \quad (3.9)$$

where $v_{f,y}^{\text{available cap}}$ is the total initial and invested capacity and $v_{f,k,t_k}^{\text{flow}}$ is the flow at timestep t_k of representative period k . This constraint is active for transport flows $f \in F^t$, as non-transport flows are bounded below by zero, while their upper bound is enforced implicitly through the asset capacity constraint.

The storage balance constraint tracks the energy stored in each non-seasonal storage asset across consecutive timesteps, ensuring energy conservation over time:

$$v_{a,k,t_k}^{\text{storage}} = v_{a,k,t_{k-1}}^{\text{storage}} + p_{t_k}^{\text{dur}} \cdot \left(p_{a,y}^{\text{eff in}} \cdot \sum_{f \in F_{a,y}^{\text{in}}} v_{f,k,t_k}^{\text{flow}} - \frac{1}{p_{a,y}^{\text{eff out}}} \cdot \sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k}^{\text{flow}} \right) \quad (3.10)$$

$$\forall a \in A^s \setminus A^{\text{ss}}, y \in Y, k \in K, t_k \in T_k$$

where $p_{a,y}^{\text{eff in}}$ is the charging efficiency and $p_{a,y}^{\text{eff out}}$ is the discharging efficiency, both in per unit. Incoming flows increase stored energy proportionally to charging efficiency, while outgoing flows reduce it by the inverse of the discharging efficiency. The storage level is bounded above by the available storage energy capacity and below by zero. The balance applies to every timestep within the representative period. For the first timestep, the initial level is defined by the cycling constraint described below. The storage level is tracked within each representative period for all storage assets which are not seasonal storage assets A^{ss} .

Storage assets can be modelled as seasonal storage, meaning they can shift energy not only within a representative period but also across the full timeframe. Without an inter-period linkage, each representative period would be solved in isolation and a storage asset could not charge in one representative period and discharge in another. This is addressed through two coupled storage balances: an intra-period balance that tracks the storage level within each representative period (as above), and an inter-period balance that tracks the storage level across the chronological sequence of periods over the full timeframe. Each actual period is linked to the representative periods that approximate it through mapping weights, allowing seasonal storage assets to buffer energy over longer timescales.

The inter-period storage balance constraint tracks the storage level of seasonal storage assets across the chronological sequence of all actual periods in the timeframe:

$$v_{a,p_y}^{\text{storage ip}} = v_{a,p_{y-1}}^{\text{storage ip}} + \sum_{k \in K} p_{p_y,k}^{\text{map}} \cdot \sum_{t_k \in T_k} p_{t_k}^{\text{dur}} \cdot \left(p_{a,y}^{\text{eff in}} \cdot \sum_{f \in F_{a,y}^{\text{in}}} v_{f,k,t_k}^{\text{flow}} - \frac{1}{p_{a,y}^{\text{eff out}}} \cdot \sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k}^{\text{flow}} \right) \quad (3.11)$$

$$\forall a \in A^{\text{ss}}, y \in Y, p_y \in P_y$$

where $v_{a,p_y}^{\text{storage ip}}$ is the inter-period storage level at the end of period p_y , $p_{p_y,k}^{\text{map}}$ is the mapping weight of representative period k for actual period p_y and P_y is the set of all actual periods in the timeframe at milestone year y .

The cycling constraints ensure that storage cannot be artificially created or lost over the modelled horizon. Since no initial storage level is defined in this study, the storage level at the end of a period is used as the initial level for its first timestep. For non-seasonal storage this applies within each representative period, and for seasonal storage it applies across the full timeframe. The full cycling formulations are provided in Appendix A.2.

The conversion balance constraint governs energy transformation at conversion assets such as electrolyzers and hydrogen-to-power conversion. It ensures that the total energy input to a conversion asset equals the total energy output, scaled by the conversion efficiency:

$$p_{a,y}^{\text{eff}} \cdot \sum_{f \in F_{a,y}^{\text{in}}} v_{f,k,t_k}^{\text{flow}} = \sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k}^{\text{flow}} \quad \forall a \in A^{\text{cv}}, y \in Y, k \in K, t_k \in T_k \quad (3.12)$$

where $p_{a,y}^{\text{eff}}$ is the efficiency of the conversion asset in per unit, defined as the ratio of energy output to energy input.

The formulations above assume uniform hourly temporal resolution for all assets and flows. In scenarios where hydrogen assets operate at a coarser resolution, Tulipa applies its flexible temporal resolution feature to handle the coupling between different timestep lengths (Gao et al., 2025). The practical effect on model behaviour is described in Section 4.5.4.

The ramping constraints limit the rate at which the output of an asset can change between consecutive timesteps. It consists of a maximum ramping rate up and a maximum ramping rate down:

$$\sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k}^{\text{flow}} - \sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k-1}^{\text{flow}} \leq p_{a,y}^{\text{ramp up}} \cdot v_{a,y}^{\text{available cap}} \quad \forall a \in A^{\text{ramp}}, y \in Y, k \in K, t_k \in T_k \quad (3.13)$$

$$\sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k}^{\text{flow}} - \sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k-1}^{\text{flow}} \geq -p_{a,y}^{\text{ramp down}} \cdot v_{a,y}^{\text{available cap}} \quad \forall a \in A^{\text{ramp}}, y \in Y, k \in K, t_k \in T_k \quad (3.14)$$

where $p_{a,y}^{\text{ramp up}}$ and $p_{a,y}^{\text{ramp down}}$ are the maximum ramping rates in per unit/hour, expressed as a fraction of the available capacity for assets that have ramping constraints defined and activated A^{ramp} .

The DC optimal power flow constraint replaces the free routing assumption by enforcing the physical laws governing power flow through the electricity network. In the base case and linepacking scenarios, electricity flows on transmission lines are restricted only by the transport flow capacity constraints described above, and the model is free to route power anywhere within these capacity limits regardless of network physics. The DC-OPF constraint relates the flow on each electricity transmission line to the voltage phase angle difference between its two endpoint nodes, scaled by the line's reactance:

$$v_{f,k,t_k}^{\text{flow}} = \frac{p^{\text{base}}}{p_{f,y}^{\text{reactance}}} \cdot \left(v_{a^{\text{from}},k,t_k}^{\text{angle}} - v_{a^{\text{to}},k,t_k}^{\text{angle}} \right) \quad \forall f \in F^{\text{dc-opf}}, y \in Y, k \in K, t_k \in T_k \quad (3.15)$$

where p^{base} is the power system base in MVA, $p_{f,y}^{\text{reactance}}$ is the reactance of transmission line f normalized to per unit and $v_{a^{\text{from}},k,t_k}^{\text{angle}}$ and $v_{a^{\text{to}},k,t_k}^{\text{angle}}$ are the voltage phase angles at the sending and receiving nodes respectively. One node in the network is designated as the reference bus with its angle fixed at zero, from which all other angles are determined. This constraint will be activated on all AC electricity lines creating the subset $F^{\text{dc-opf}}$.

3.4. Evaluation metrics

The four scenarios, defined in Section 4.5, are evaluated and compared using the metrics defined below, each reported for milestone years 2030 and 2040. The metrics are derived from the decision variables and dual values of the optimisation presented in Section 3.3. Dual values are denoted λ . The dual of a constraint is the change in total system cost that would result from relaxing that constraint by one unit at the optimal solution.

Several metrics require post-processing before they can be compared across scenarios and years. The raw solver output includes a scaling from the representative period weight, the timestep duration, and, for dual values, the operational discount factor. Metrics derived from dual variables are corrected for all three, while metrics from flow variables are summed with the representative period weights and

timestep durations, which scales them to a full year. The specific corrections are described per metric below.

The metrics answer the research question in two steps. Sub-question 4 asks where hydrogen production is cost-optimal under each representation, and the electrolyser investment location and capacity metric answers it directly. The main research question asks how the representations influence that outcome, which requires showing the mechanism between the two. The locational energy costs and the marginal value of line capacity establish that mechanism on the electricity side, since they are the values through which a representation can make one location cheaper than another. Offshore wind curtailment shows the physical consequence of the same constraints. The dispatch and investment costs quantify what the mechanism costs the system, which is what the model minimizes and therefore the reason siting changes at all. Line utilisation, flexible operation, and within-block electricity concentration show how the representations change operation rather than siting, which is what separates the linepacking effect from the DC-OPF effect. Together they trace the path from the representation being tested to the siting decision it produces.

The metrics used to verify and validate the model are described at the end of this section, and the full checks are reported in Appendix C.

Electrolyser investment location and capacity is the primary metric, as the cost-optimal location of hydrogen production is what the main research question needs for its final answer. It is derived from the investment variable for electrolyser assets and reported per candidate investment node: the offshore hubs and onshore hydrogen demand nodes. Results are also aggregated to total offshore versus onshore capacity per scenario and milestone year to enable direct cross-scenario comparison.

The implicit locational energy costs are the values through which network representation influences electrolyser siting, so they explain why investment occurs where it does. They are derived from the dual variables of the consumer balance constraint at electricity grid and hydrogen backbone nodes. In a cost-minimisation LP, these dual variables represent the marginal system cost of serving one additional unit of demand at each node, and are formally equivalent to locational marginal prices (Aravena et al., 2021). Both electricity representations produce these locational prices, and in both the prices separate where line capacity binds. DC-OPF constrains the network further, so prices are expected to separate more strongly. Farahmand et al. (2024) apply the same approach in a North Sea investment model, relaxing the problem to a pure LP specifically to extract clean nodal dual variables. These values are not real market prices, but they are meaningful system costs: they reflect relative scarcity at each location, and differences between nodes and between scenarios are the signal. They explain why the model invests in electrolyzers at specific locations, and how DC-OPF changes the cost landscape relative to the transport model.

The raw dual value of the consumer balance constraint is scaled by the same representative period weight, timestep duration, and operational discount factor that multiply the flow's operational cost in Equation (3.6). In a linear programming problem, the dual of a constraint equals the marginal cost of meeting that constraint, so it carries the identical scaling. To get the real hourly nodal price at consumer asset a at timestep t_k of representative period k , these three factors need to be divided out:

$$\lambda_{a,k,t_k}^{\text{nodal price}} = \frac{\lambda_{a,k,t_k}^{\text{cbc}}}{p_y^{\text{disc op}} \cdot p_k^{\text{rp weight}} \cdot p_{t_k}^{\text{dur}}} \quad \forall a \in A^c, y \in Y, k \in K, t_k \in T_k \quad (3.16)$$

where $\lambda_{a,k,t_k}^{\text{cbc}}$ is the raw dual of the consumer balance constraint and $p_y^{\text{disc op}}$ is defined in Equation (A.7) (Appendix A.1). The average yearly nodal price is the weighted mean of these hourly prices, taking the representative period weighting and timestep duration into account:

$$\bar{\lambda}_{a,y}^{\text{nodal price}} = \frac{\sum_{k \in K} \sum_{t_k \in T_k} \left(p_k^{\text{rp weight}} \cdot p_{t_k}^{\text{dur}} \right) \lambda_{a,k,t_k}^{\text{nodal price}}}{\sum_{k \in K} \sum_{t_k \in T_k} \left(p_k^{\text{rp weight}} \cdot p_{t_k}^{\text{dur}} \right)} \quad \forall a \in A^c, y \in Y \quad (3.17)$$

The denominator is the amount of represented hours in the year. Timesteps in which dummy producers are active are excluded from both sums. Because $p_y^{\text{disc op}}$ differs between milestone years, the raw dual

is not comparable across years. Dividing it out gives an undiscounted price, so $\bar{\lambda}_{a,y}^{\text{nodal price}}$ is comparable both within and across milestone years.

The marginal value of line capacity identifies where and when the electricity network limits power delivery. It is the mechanism that creates locational cost differences: by enforcing physical flow, DC-OPF makes network limits bind more often and with higher duals than under the transport model, which separates electricity prices between locations and thereby influences electrolyser siting. It is measured by the dual of the transport flow limit constraint $\lambda_{f,k,t_k}^{\text{tflc}}$. This dual represents the marginal reduction in system cost that one additional unit of capacity on that line would provide. A high value indicates the line is congested and constrains the system, since relieving it would meaningfully reduce cost. A value of zero means the line has spare capacity and is not limiting. Like the nodal price, this dual carries the representative period weight, the timestep duration, and the operational discount factor, and is corrected by the same division as in Equation (3.16):

$$\lambda_{f,k,t_k}^{\text{line}} = \frac{\lambda_{f,k,t_k}^{\text{tflc}}}{p_y^{\text{disc op}} \cdot p_k^{\text{rp weight}} \cdot p_{t_k}^{\text{dur}}} \quad \forall f \in F^t, y \in Y, k \in K, t_k \in T_k \quad (3.18)$$

for transport flows f in milestone year y . The corrected value is in EUR/MWh. It is averaged over the included hours, giving an average hourly constraint strength comparable across scenarios and years. It is calculated identically to Equation (3.17) but for transport flows $f \in F^t$ instead of consumer assets $a \in A^c$. A line is counted as binding in an hour when its dual value is above numerical tolerance, which avoids counting solver round-off as binding.

Dispatch cost shows whether enforcing DC-OPF physics or linepacking flexibility changes how expensively the system is operated, separate from investment. It is computed from the flow variables, summing the operational cost over all real generation, storage, and conversion flows. Unlike the objective term in Equation (3.6), the operational discount factor is not applied, so the result is an undiscounted annual cost:

$$C_y^{\text{disp}} = \sum_{f \in F_y^{\text{op}}} \sum_{k \in K} \sum_{t_k \in T_k} p_k^{\text{rp weight}} \cdot p_{t_k}^{\text{dur}} \cdot p_{f,y}^{\text{op cost}} \cdot v_{f,k,t_k}^{\text{flow}} \quad \forall y \in Y \quad (3.19)$$

where F_y^{op} is the set of flows from assets with operational costs. This includes producer, storage and conversion assets, excluding dummy producer flows. The representative period weight $p_k^{\text{rp weight}}$ and timestep duration $p_{t_k}^{\text{dur}}$ scale the hourly flows to a full year, so C_y^{disp} is comparable across scenarios and milestone years.

Investment cost reveals whether the network representations shift capital spending between offshore and onshore or between carriers, complementing the primary location metric. It is the investment cost parameter times the invested capacity, summed over the investable assets and flows. It is reported per milestone year as raw capital cost, without annuitisation or discounting:

$$C_y^{\text{inv}} = \sum_{a \in A_y^{\text{inv}}} p_{a,y}^{\text{inv cost}} \cdot v_{a,y}^{\text{inv}} + \sum_{f \in F_y^{\text{inv}}} p_{f,y}^{\text{inv cost}} \cdot v_{f,y}^{\text{inv}} \quad \forall y \in Y \quad (3.20)$$

Unlike the corresponding objective terms (Equations (3.2) and (3.4)), the discounting factor is not applied, so C_y^{inv} is the undiscounted direct investment in year y . Fixed operating costs are excluded, since they are a constant fraction of investment cost and do not change the relative comparison between locations or scenarios.

Line utilisation shows how intensively lines in the network are used. It is used to see how congestion impacts the ability of the network to use its capacity. It is the absolute flow on a line divided by its capacity:

$$U_{f,k,t_k}^{\text{flow}} = \frac{|v_{f,k,t_k}^{\text{flow}}|}{v_{f,y}^{\text{available cap}}} \quad \forall f \in F^t, y \in Y, k \in K, t_k \in T_k \quad (3.21)$$

where $v_{f,k,t_k}^{\text{flow}}$ is the flow on transport flow f and $v_{f,y}^{\text{available cap}}$ is its available capacity. The absolute value is taken because transport flows are bidirectional. The yearly utilisation is again the average of these hourly utilisation values, taking the representative period weighting and timestep duration into account. It is calculated with the same formula as Equation (3.17) but with the hourly utilisation $U_{f,k,t_k}^{\text{flow}}$ instead of $\lambda_{a,k,t_k}^{\text{nodal price}}$. It shows how heavily a flow is used. Utilisation indicates the usage of a line, while the marginal value of line capacity in Equation (3.18) indicates whether this usage constrains the system.

Offshore wind curtailment shows how much available offshore wind the system does not use. It links directly to the siting question, since stranded offshore wind can be converted to hydrogen at the hub instead. It is the share of available offshore wind generation that is not dispatched. Available generation is the offshore wind capacity times its hourly availability profile, summed over the year. Curtailment is one minus the ratio of dispatched to available offshore wind generation:

$$E_y^{\text{curt}} = 1 - \frac{\sum_{a \in A^{\text{ow}}} \sum_{k \in K} \sum_{t_k \in T_k} p_k^{\text{rp weight}} \cdot p_{t_k}^{\text{dur}} \cdot \sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k}^{\text{flow}}}{\sum_{a \in A^{\text{ow}}} \sum_{k \in K} \sum_{t_k \in T_k} p_k^{\text{rp weight}} \cdot p_{t_k}^{\text{dur}} \cdot p_{a,k,t_k}^{\text{availability profile}} \cdot v_{a,y}^{\text{available cap}}} \quad \forall y \in Y \quad (3.22)$$

where $A^{\text{ow}} \subseteq A^{\text{p}}$ is the set of offshore wind assets. The numerator is the dispatched offshore wind: the asset output flow summed over the year. The denominator is the available offshore wind: the availability profile times available capacity. The representative period weight and timestep duration scale both sums to a full year.

Within-block electricity concentration captures the flexibility that linepacking specifically enables. In the linepacking scenarios, the hydrogen balance is enforced over each four-hour block rather than each hour, so an electrolyser can vary its electricity consumption across the four hours while still delivering hydrogen at a constant block rate. This metric measures the extent to which the electrolyser uses this ability. For each four-hour block in which the electricity price differs across its hours, the share of the block's total electricity consumption drawn in the cheapest hour is calculated. If the electrolyser spread consumption evenly, each hour would draw 25% of the total electricity consumption across the block. A cheapest-hour share above 25% shows the electrolyser is concentrating consumption in the cheapest hour and reducing it in expensive hours. This behaviour is impossible in the scenarios without linepacking, where the hourly hydrogen balance forces a constant hourly consumption, so this metric isolates the operational effect of linepacking.

Flexible operation measures whether the electrolyser behaves as rational price-responsive load, concentrating consumption in cheap hours and backing off when electricity is expensive. It is reported as the two ratios described below.

The hourly price ratio is the ratio between nodal prices during operation against average nodal prices. First the average nodal price over the year is calculated, which is the average price the electrolyser would pay if it ran at a constant rate. Then the average price at which the electrolyser actually operates is calculated, found by weighting each hour by the electricity it consumed in that hour. Dividing the second by the first gives the flexible operation ratio. A ratio of one means the electrolyser pays the average price and runs evenly across hours. A ratio below one means it shifts consumption into cheaper hours and avoids expensive ones, so the lower the ratio the more flexibly it operates.

The block price ratio is the same measure computed over fixed four-hour blocks instead of single hours. It isolates the coarse timescale: which blocks the electrolyser chooses to run in, rather than how it arranges consumption inside a block. Each block is treated as one step, with a single price equal to the mean of its four hourly prices and a consumption equal to the total across them, and the ratio is formed as above. The blocks are the same fixed windows in every scenario, so the ratio is comparable across all four. The transport scenarios have no hydrogen blocks, so their hourly consumption is grouped into these same windows for the comparison. Because block selection is available with or without linepacking, this ratio separates the block-level choice, shared by all scenarios, from the within-block shifting that only linepacking permits.

The remaining checks confirm the model is correct and plausible rather than answering the research question.

The energy balance equations are a verification rather than an analysis metric. For each scenario and milestone year, the annual sum of all electricity flows and all hydrogen flows must close to zero, with energy removed only through the storage losses and conversion efficiencies that are explicitly defined. The residual measures numerical accuracy. The two balance equations and the per-scenario residuals are given in Appendix C.

The electrolyser capacity factor is a validation metric. It checks whether the cost-optimal electrolyser fleet operates at a realistic utilisation, confirming the model behaves sensibly. It is the annual hydrogen output divided by the maximum possible output:

$$\phi_y = \frac{\sum_{a \in A^{\text{el}}} \sum_{k \in K} \sum_{t_k \in T_k} p_k^{\text{rp weight}} \cdot p_{t_k}^{\text{dur}} \cdot \sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k}^{\text{flow}}}{\sum_{a \in A^{\text{el}}} v_{a,y}^{\text{available cap}} \cdot 8736} \quad \forall y \in Y \quad (3.23)$$

where $A^{\text{el}} \subseteq A^{\text{cv}}$ is the set of electrolyser assets. The numerator is the annual hydrogen output: the asset output flow scaled to a full year. The denominator is the maximum possible output: the available capacity times the 8736 hours of the trimmed year. Capacity is defined on the hydrogen output flow. The year is trimmed to 8736 hours, 364 days, so that it divides into whole weeks for the temporal clustering described in Section 4.4. The final 24 hours are excluded. Realistic utilisation is judged in two ways. Physically, a factor near one would indicate inflexible baseload operation and a factor near zero stranded capacity, so a cost-optimal flexible electrolyser should sit between these extremes. Against the literature, studies that let the model choose the capacity factor report values from 30 to 33% where electrolysers are oversized for flexibility (Martínez-Gordón et al., 2022), 55 to 61% where they follow an offshore wind profile (Travaglini et al., 2025), and 70% and above where hydropower balances the wind (Bødal et al., 2024). Studies that assume the capacity factor as an input instead use 50 to 67% (Farahmand et al., 2024; Gea-Bermúdez et al., 2023; Jang et al., 2022). The factor here is an optimisation outcome, so the first group is the relevant comparison.

These metrics are presented in Chapter 5 for both milestone years and compared across scenarios. Before the results are analysed, the model is verified and validated. Verification checks that the model calculates as intended, and validation checks that its outputs are physically and economically plausible. Without both, a difference between scenarios could reflect a modelling error rather than the network representation being tested, so these checks are what allow the scenario comparison to be read as a real effect. Three verification checks are applied: energy conservation across every scenario and year, reproduction of the preparatory run by the base case on the fixed network, and a check that the corrected nodal price equals the operational cost of the marginal producer at an uncongested node. Two validation checks are applied: the electrolyser capacity factor, which tests whether the cost-optimal fleet operates at a realistic utilisation rather than as stranded or baseload capacity, and a comparison of the corrected nodal prices against Farahmand et al. (2024), who model the same region and extract prices from duals in the same way. All five checks are passed. They are reported in full in Appendix C.

3.5. Conclusion on methodology

This chapter set out the modelling approach used to answer the research question. Energy system optimisation with a perfect-foresight, linear programming formulation was chosen because the study needs a least-cost siting outcome under many interacting constraints. The Tulipa Energy Model was selected because it provides mathematical structures for both modelling choices the research question evaluates: a transport and a DC-OPF electricity representation, and a flexible temporal resolution that can approximate linepacking. The formulation and the evaluation metrics defined here are the applied to the North Sea system in the next chapter.

4

Case Study

4.1. Study area and system scope

As outlined in Chapter 1, the North Sea is the focal point of Europe's offshore wind expansion, with targets of approximately 120 GW by 2030 and over 300 GW by 2050 (Energy Ministers of the North Seas Countries, 2023). The region involves eight countries with interconnected electricity grids and a planned hydrogen backbone, making it a relevant geography for studying the interaction between offshore wind integration, electricity transmission, and hydrogen production. This study models an integrated electricity and hydrogen system covering Norway, Denmark, Germany, the Netherlands, Belgium, Luxembourg, France, and the United Kingdom.

The model is built for three milestone years: 2030, 2040, and 2050. The main scenario comparison, however, covers only 2030 and 2040. Demand and capacity projections in this study are primarily based on the Ten-Year Network Development Plan (TYNDP) 2024, a European system planning study published by ENTSO-E (European Network of Transmission System Operators for Electricity and Gas [ENTSO-E & ENTSOG], 2024). For 2050, the projections within this dataset are not internally consistent: the demand and the supply projections are drawn from different files within the same study and do not align, producing a structural supply-demand gap. Because the model optimises all milestone years simultaneously, this gap would distort the 2030 and 2040 investment decisions if 2050 were included in the same run. The scenario runs are therefore limited to 2030 and 2040, while 2050 is examined separately as an exploratory analysis in Appendix D. The data construction described in this chapter covers all three milestone years, as the full dataset underlies both the main analysis and the exploratory 2050 results. The spatial extent of the modelled system and the locations of the thirteen offshore energy hubs are shown in Figure 4.1.

The onshore system is spatially aggregated to NUTS-2 regional resolution, providing a balance between spatial detail and computational feasibility. Regions with less relevance to North Sea energy flows are aggregated to the coarser NUTS-1 level, shown in darker grey in Figure 4.1. These regions are downloaded from Eurostat (2021). The offshore network consists of thirteen energy hubs located in the North Sea, each collecting electricity from multiple nearby OWFs. Hubs can be connected to each other and to onshore nodes through offshore electricity cables and hydrogen pipelines, with the model optimising which connections to invest in.

The model simultaneously represents three interconnected systems: the onshore high-voltage electricity transmission grid, the planned European hydrogen backbone, and the offshore wind and hub network. Together these form a single integrated optimisation problem in which investment decisions and hourly operation are optimised across the milestone years. The construction of each system component is described in the following subsections.

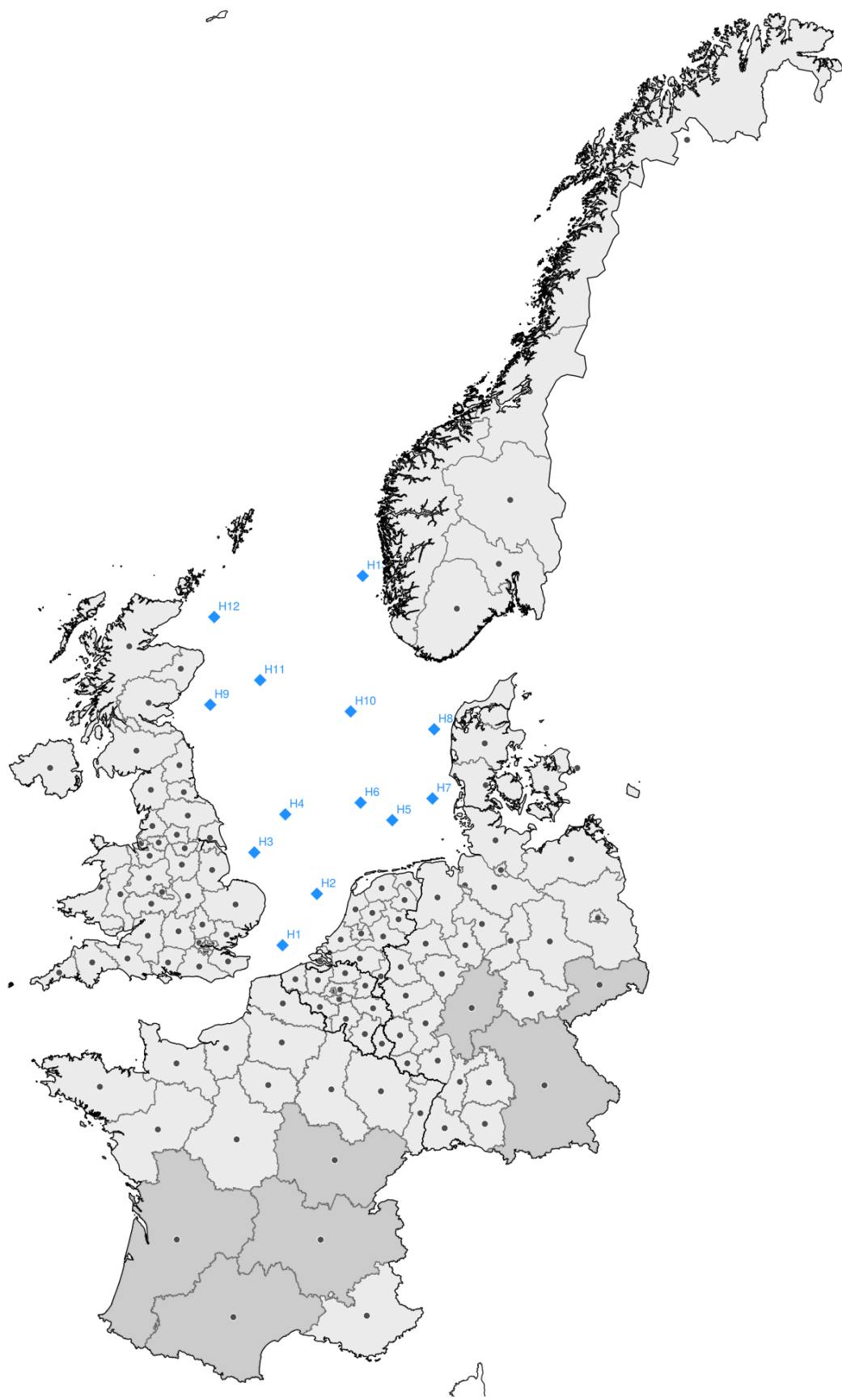


Figure 4.1: Included regions and hub locations of countries near the North Sea. Darker grey regions use NUTS-1 rather than NUTS-2 resolution. For regions where NUTS-2 and NUTS-1 boundaries are identical, the colour is light grey.

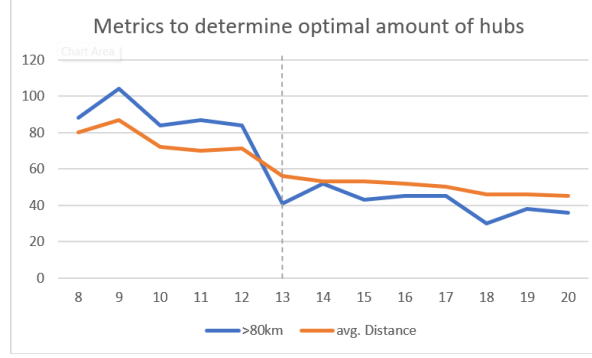


Figure 4.2: Distance-based criteria for selecting the number of offshore hubs, evaluated across $k = 8$ to $k = 20$. The two metrics are the number of OWFs assigned to a hub more than 80 km away, and the average distance from wind farms to their assigned hub. Both improve substantially up to $k = 13$, after which further increases yield only marginal reductions.

4.2. Spatial data construction

This section describes the construction of the three spatial components of the model: the offshore hub network, the onshore electricity grid, and the hydrogen backbone. Each is derived from independent data sources and processed separately before being integrated into the optimisation model.

4.2.1. Offshore network

The offshore network consists of offshore energy hubs: collection points where electricity from multiple OWFs is bundled and either transmitted onshore as electricity or (partly) converted to hydrogen for pipeline transport (NSWPH, 2024). Concentrating energy from multiple OWFs at a single hub reduces the total length of connecting cables and enables economies of scale in offshore infrastructure.

The locations and capacities of current and future OWFs were obtained from the NSEC TIMELINES database (North Sea Energy Cooperation [NSEC], 2025). Polygon geometries were converted to centroids using QGIS (Dawson et al., 2026). QGIS is used throughout this study for all spatial assignments of asset and network coordinates to NUTS regions. Missing OWF capacities, for most of the UK wind farms, were supplemented from operator and government sources. Where projected national capacity targets exceeded the sum of defined OWF capacities, the remaining capacity was distributed proportionally across planned search areas and existing locations, assuming that sites can be repurposed and expanded with a more advanced fleet as turbines reach end-of-life. OWFs located outside the North Sea boundaries defined in International Hydrographic Organization (IHO, 1953) were excluded.

All distances in this study are calculated using the haversine formula, accounting for the curvature of the Earth. Hub locations were determined using a capacity-weighted k-means clustering algorithm. K-means is well-suited for this purpose as the input data consists of geographical locations where physical distance is the primary criterion, and the method is computationally efficient and widely used in literature (Martínez-Gordón et al., 2022). Weighting by OWF capacity ensures that high-capacity farms have a greater influence on hub placement, reflecting that cable costs depend on both length and capacity. Since hub locations should support the full future offshore network, the algorithm was applied to the 2050 OWF scenario, assuming complete knowledge of future development when planning to build hubs. K-means requires the number of clusters to be specified in advance. An elbow method analysis suggested a lower bound of $k = 8$, after which the appropriate number of hubs was determined by evaluating two criteria across $k = 8$ to $k = 20$: the number of OWFs assigned to a hub more than 80 km away, and the average distances from the OWFs to a hub. The 80 km threshold reflects the limit where HVAC cables are more cost-effective than HVDC cables (Martínez-Gordón et al., 2022). As shown in Figure 4.2, both metrics improve substantially at $k = 13$, with the number of OWFs beyond 80 km dropping from over 80 to 41 and average distance falling from approximately 70 km to 56 km. After this, further increases in k yield less substantial decreases in the criteria. Thirteen hubs were therefore selected.

Since k-means is a heuristic algorithm, repeated runs may produce slightly different hub locations. As this study focuses on the effect of network representations rather than the precise geographical config-

uration of offshore hubs, small variations in hub locations are assumed to have no substantial influence on the conclusions. The OWF capacities for each milestone year are assigned to the hub of their corresponding cluster. Water depth at each OWF location was extracted from the EMODnet bathymetry dataset (European Marine Observation and Data Network, 2024), which determines whether fixed-bottom or floating foundation costs apply, as discussed in Section 4.3.1.

The potential electricity cable and hydrogen pipeline connections between offshore hubs, and between hubs and onshore connection points, were defined using Delaunay triangulation on the hub locations and current onshore DC-interconnection points. This method connects each hub to its spatially close neighbours without producing crossing connections, providing a realistic and non-redundant set of candidate infrastructure links. All OWFs are connected to hubs, from which electricity and hydrogen can be transmitted to shore. Direct connections from wind farms to the mainland are not represented in the model. All connections between offshore hubs and between hubs and onshore landing points are modelled as HVDC links, consistent with the infrastructure designs used in comparable North Sea studies (Löhr et al., 2023; Martínez-Gordón et al., 2022). Investment and fixed costs for these offshore connections are taken from the NSWPH dataset (Hartvig et al., 2025).

4.2.2. Onshore electricity network

The onshore electricity network is constructed at NUTS-2 and NUTS-1 regional resolution. Country-level aggregation has been shown to suppress the differences between transport and DC-OPF modelling due to the loss of internal congestion (Cao et al., 2021). Therefore a finer resolution is necessary to preserve the congestion dynamics this study aims to capture. The onshore electricity network is constructed by aggregating the European high-voltage grid (220-750 kV) to the regional NUTS resolution, based on transmission line data from Xiong et al. (2025). NUTS-2 regions provide a balance between spatial detail and computational feasibility, and align with the resolution of demand and generation data used as model inputs across the eight countries defined in Section 4.1. Both AC transmission lines and existing DC interconnectors from the dataset are included in the network representation. For regions that are not at the border of the North Sea or to the included countries (specifically southern France and south-eastern Germany) NUTS-1 aggregation is used instead of NUTS-2. This ensures that detailed network congestion dynamics are focused on the areas most relevant to offshore hydrogen production, while keeping the model size manageable.

The spatial resolution of the AC grid was simplified using the `ElectricityNetworkReduction.jl` Julia package, which is developed as part of the Tulipa Energy Model (Soares Siqueira et al., 2026). The package aggregates the detailed bus-level network into one representative node per defined NUTS region, and derives equivalent transmission capacities and reactances between those nodes. The aggregation keeps the physical power flow behaviour of the real network. This includes the characteristic that power flow between two regions partially loads transmission lines in third regions, based on Kirchhoff's laws. This is more realistic than simply summing the capacities of lines crossing regional borders, which would overestimate real transfer capacity by ignoring these interactions.

The aggregation is performed in three steps. First, a mathematical representation of the full network is constructed, the admittance matrix, from which the PTDFs are derived. These describe how power flows between every pair of buses based on the reactance of each transmission line. Second, Kron reduction eliminates all buses within a region except one representative node, while preserving the electrical relationships between regions. Third, the equivalent capacity of each inter-regional connection is optimised such that the maximum transferable power between every pair of regions in the reduced network matches that of the original detailed network as closely as possible.

The Belgian regions BE10 and BE31 have no direct connections in the high-voltage dataset. Based on the official Elia transmission map (Elia Group, 2023), these regions are physically connected to adjacent regions via 150 kV lines, which were added manually to ensure full network connectivity. The resulting aggregated electricity network, including existing DC interconnectors and candidate offshore HVDC investment connections, is shown in Figure 4.3. Investment and fixed costs for onshore electricity transmission connections are taken from Hartvig et al. (2025).

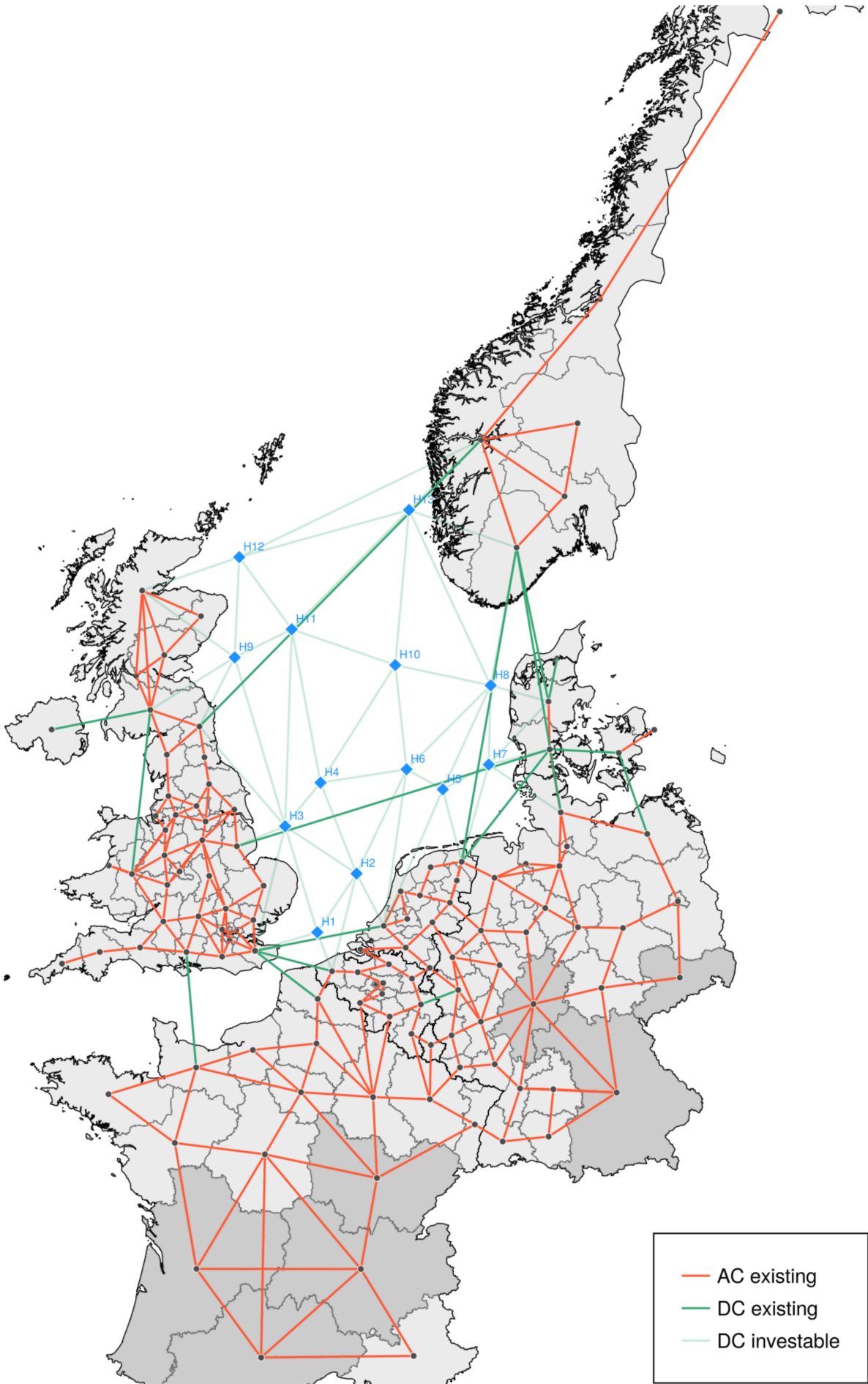


Figure 4.3: Aggregated onshore electricity network, including existing DC interconnectors and candidate offshore HVDC investment connections.

4.2.3. Hydrogen backbone

The hydrogen backbone is based on plans from the European Hydrogen Backbone (European Hydrogen Backbone [EHB], 2021a), a proposed pan-European pipeline network connecting hydrogen production, demand, and storage locations. This source is also used in Löhner et al. (2023). The network consists predominantly of repurposed natural gas pipelines, with EHB (2021a) reporting that 69% of the planned backbone infrastructure is repurposed rather than newly built. This distinction is relevant for cost assumptions, as repurposed pipelines have significantly lower investment costs than new hydrogen pipelines. The raw pipeline data was obtained from the EHB interactive map in JSON format (EHB, 2025), with which the network was aggregated to the NUTS regions. The 2050 network topology is used in all scenarios to ensure demand points across the milestone years are connected with the backbone. Precise pipeline capacities for the planned backbone are not yet fully defined. However, the European Hydrogen Backbone Implementation Roadmap (EHB, 2023) identifies several North Sea corridor projects with indicative capacities: the Dutch hydrogen network is planned for 10-15 GW, the Danish-German connection for up to 10 GW, and the offshore HyONE network for up to 30 GW. Based on these emerging plans, a base capacity of 10 GW is assumed per pipeline connection, reflecting the lower end of planned capacities for major North Sea corridors, representative of the broader range of projects described in EHB (2023). Investment and fixed costs are derived from Hartvig et al. (2025) as a weighted average of repurposed and newly built unit costs, with each connection calculated as 69% repurposed and 31% new construction, consistent with the share reported in EHB (2021a). Pipeline flows remain investable in Step 1, allowing the model to determine where additional capacity beyond the base 10 GW is cost-optimal. The resulting hydrogen backbone and candidate offshore pipeline investment connections are shown in Figure 4.4.

4.3. Assets, demand and profiles

The model draws on a range of datasets, each providing a specific part of the input. Table 4.1 summarises the main sources and what each contributes. Where necessary, sources were supplemented or values were combined and scaled, as described in the relevant subsections.

Table 4.1: Main data sources and their contribution to the model inputs.

Source	Contribution
TYNDP 2024 (ENTSO-E & ENTSOG, 2024)	Electricity and hydrogen demand profiles and peak values, national capacity projections for wind and solar, carbon prices
NSWPH (Hartvig et al., 2025; NSWPH, 2024)	Offshore hub concept, offshore wind and electrolyser cost data, electricity cable and hydrogen pipeline costs
NSEC TIMELINES (NSEC, 2025)	OWF locations and capacities
Xiong et al. (2025)	European high-voltage transmission grid topology, capacity and reactances
European Hydrogen Backbone (EHB, 2021a, 2021b, 2023, 2025)	Hydrogen pipeline network, storage locations, industrial hydrogen demand, corridor capacities
Gotzens et al. (2019)	Conventional generator and storage locations, types, and capacities
Global Wind Power Tracker (Global Energy Monitor, 2026)	Onshore wind farm locations
Alghanem and Buckley (2025)	Regional solar PV distribution
Hystories (2022)	Techno-economic cost parameters for most asset types
Renewables.ninja (Pfenninger & Staffell, 2016; Staffell & Pfenninger, 2016)	Hourly wind and solar availability profiles
ENTSO-E Transparency Platform (ENTSO-E, 2026)	Run-of-river hydro generation profiles and yearly hydro reservoir electricity generation

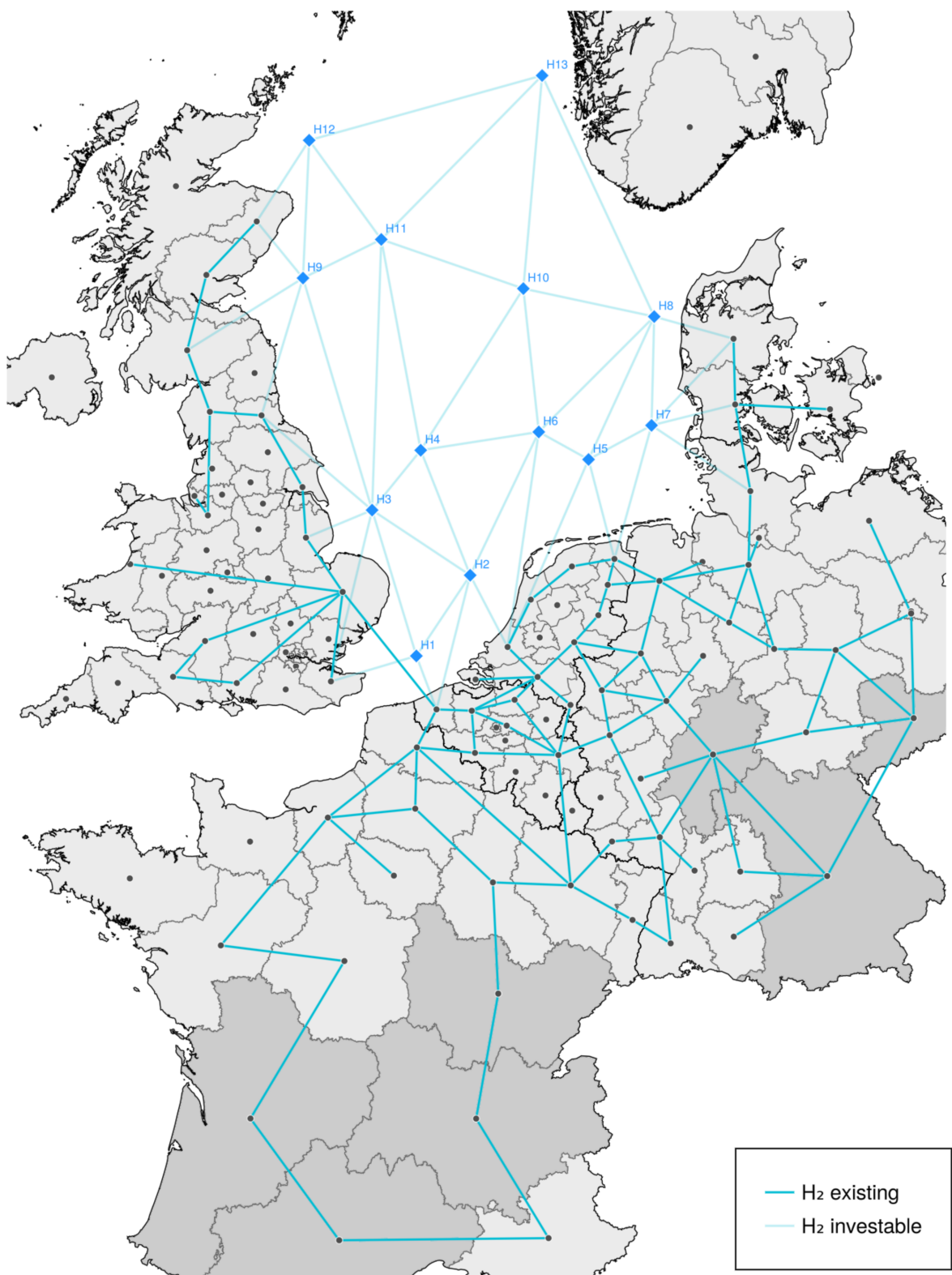


Figure 4.4: Aggregated hydrogen backbone and candidate offshore pipeline investment connections.

4.3.1. Producer assets

The electricity generation mix determines the cost and availability of electricity at each node, which directly influences where electrolyser investment becomes cost-optimal. Installed capacities and locations of centralised electricity producers are taken from Gotzens et al. (2019) and aggregated by technology type and NUTS region. The following producer types are included: coal, oil, CCGT, gas with steam turbine, combustion engine, biomass and waste, run-of-river hydro, reservoir hydro, and nuclear. Lignite and hard coal are grouped into a single coal category, with costs derived as a weighted average based on a 46/54 percent split. Similarly, biomass and waste are grouped because they share the same steam turbine technology and have a small combined share in the total generation mix. Their costs are derived as a weighted average based on a 44/56 percent split for waste and biomass respectively. The fuel and emission costs of combustion engine plants are derived as a weighted average of 37% natural gas and 63% biogas, reflecting the fuel mix observed in the dataset. Gas steam turbine costs use the same investment and fixed cost parameters as coal plants, reflecting their shared steam turbine technology, with fuel costs and emission factors adjusted to reflect natural gas combustion. Carbon prices of 113, 147, and 168 EUR/tCO₂ for 2030, 2040, and 2050 respectively are applied to all generators with CO₂ emissions, taken from the TYNDP 2024 dataset (ENTSO-E & ENTSG, 2024).

National onshore wind capacities are taken from the TYNDP dataset (ENTSO-E & ENTSG, 2024) and distributed across the NUTS regions in proportion to the existing regional pattern of wind farm locations from Global Energy Monitor (2026). Solar PV capacities per NUTS region are derived by applying national percentage distributions from Alghanem and Buckley (2025) to projected national totals from the TYNDP dataset (ENTSO-E & ENTSG, 2024). Offshore wind is described in Section 4.2.1.

Investment, fixed, and operational costs for 2030, 2040, and 2050 are primarily taken from Hystories (2022), with missing values supplemented from Hatton et al. (2024) and Iisazeyen et al. (2026). The operational costs are based on fuel costs, emissions, carbon prices, variable costs and efficiencies of power plants. Offshore wind costs are depth-dependent: fixed-bottom installations use cost data from Hartvig et al. (2025) for depths up to 70 metres, while floating foundations at greater depths are based on Montes et al. (2025).

Over the milestone years, only off- and onshore wind and solar PV capacity grows. Fossil fuel plants are assumed not to expand due to environmental regulations. Nuclear capacity is assumed fixed given uncertain policy targets and societal opposition in several North Sea countries. Reservoir and run-of-river hydro are assumed to be already fully utilised. Biomass capacity is similarly fixed due to limited feedstock availability.

None of the producer assets are investable in the model. This keeps the generation fleet fixed and isolates the effect of network representations on electrolyser investment location, which is the focus of this research. Investment and fixed costs for these assets are still included in the objective function for completeness, but since they are fixed across all scenarios they do not affect the relative comparison between scenarios. Technical lifetimes for all non-investable assets are taken from Hystories (2022) and, like their fixed costs, are identical across all scenarios. Economic lifetimes are set equal to technical lifetimes, as asset-specific economic lifetime data was not available. While this affects absolute investment cost levels through the annualisation factor, the assumption is applied consistently across all scenarios and assets, ensuring the scenario comparison is unaffected. Ramping constraints are only activated for nuclear assets, where they approximate baseload behaviour by limiting how quickly output can change between consecutive hours.

Detailed cost parameters for all producer, storage and conversion asset types, including derived values for grouped categories, are provided in Appendix B.

4.3.2. Storage assets

The model includes five storage asset types: batteries and pumped hydro storage (PHS) for electricity, and hydrogen storage in salt caverns, above-ground tanks, and depleted fields. Installed capacities for batteries and PHS are taken from Gotzens et al. (2019) and aggregated to the NUTS regions. Since battery capacities in this dataset did not align with projected national targets, the national targets from ENTSO-E & ENTSG (2024) are redistributed proportionally across NUTS regions based on the regional distribution in Gotzens et al. (2019). For UK targets, scenarios from National Energy System

Operator (NESO, n.d.) are used. Hydrogen storage locations and capacities are derived from the EHB interactive map (EHB, 2025), consistent with the hydrogen backbone construction described in Section 4.2.3.

Since plant-level energy capacity data is not fully available in the datasets, fixed energy-to-power ratios are applied. Batteries are assigned a ratio of 2 MWh/MW and PHS 6 MWh/MW, both consistent with Hystories (2022). Hydrogen storage ratios are also taken from Hystories (2022), as capacity data for individual storage sites was not consistently available from the EHB interactive map: salt caverns are assigned 268 MWh/MW, depleted fields 800 MWh/MW, and above-ground tanks 48 MWh/MW. All storage costs are also from Hystories (2022).

None of the storage assets are investable. As with the producer assets, this keeps the existing storage fleet fixed across scenarios and ensures that differences in results between scenarios are driven solely by network representation choices rather than storage investment decisions. Storage assets are permitted to charge and discharge simultaneously within a timestep, as restricting this would require binary variables and convert the problem to a MILP.

4.3.3. Conversion assets

The model includes four conversion asset types: electrolyzers, hydrogen combined cycle gas turbines (H_2 -CCGT), hydrogen gas turbines, and fuel cells. All conversion assets are investable, meaning the model optimises how much capacity to build at each location.

Electrolyzers are the central investment decision in this research, as their cost-optimal location is the primary outcome of interest. Possible investment locations are all thirteen offshore hubs and all onshore hydrogen demand nodes, representing industrial clusters with direct access to the hydrogen backbone. Restricting candidate locations to these nodes keeps the investment problem tractable and reflects that electrolyzers are most plausibly built where hydrogen demand and backbone access coincide. For electrolyzers, offshore installations have additional costs for marine infrastructure and integration with offshore platforms, so costs are differentiated and taken from Hartvig et al. (2025) for both onshore and offshore configurations. The other conversion asset techno-economic parameters and lifetimes are taken from Hystories (2022). Economic lifetimes are set equal to technical lifetimes, as discussed in Section 4.3.1. Electrolyzers and H_2 -CCGT are assigned a lifetime of 25 years, hydrogen gas turbines 30 years, fuel cells 20 years.

For hydrogen-to-electricity conversion assets (H_2 -CCGT, hydrogen gas turbine, and fuel cell) no reliable projections exist yet on where such assets will be integrated into the energy system. These assets are therefore also treated as investment decisions, with possible locations limited to onshore hydrogen demand nodes. This reflects the assumption that hydrogen-to-electricity conversion will be located at industrial hydrogen and electricity demand clusters, where backbone pipeline connections are available and local electricity demand is high. No investment limits are imposed on electrolyzers or conversion assets, so the model is free to place capacity wherever it is cost-optimal without artificial constraints forcing it to alternative locations.

4.3.4. Demand

Electricity demand profiles and peak demand values for 2030 and 2040 are taken from the ENTSO-E TYNDP 2024 dataset (ENTSO-E & ENTSG, 2024), using the National Targets (NT) scenario. The hourly profiles are based on weather and demand year 2009 and are provided at national level in MW. For 2050, regional peak demands are not directly available in the NT scenario. Instead, total electricity demand in TWh/year for 2040 and 2050 is taken from the TYNDP Supply Tool, and the ratio between these two years is used as a scaling factor applied to the 2040 hourly profile. For the United Kingdom and Norway, this scaling factor was not available, so the average growth factor of the other North Sea countries (1.51) is applied.

Regional industrial hydrogen demand values are derived from demand maps in EHB (2021b), which classify NUTS-2 regions into four demand scales. Regions with demand below 1 TWh/year (the lowest scale) are excluded as negligible. For the remaining regions, initial demand values are set at the midpoint of their respective range: 3 TWh/year for the 1-5 TWh/year range and 10 TWh/year for the 5-15 TWh/year range. Regions in the highest scale have no defined upper bound, so initial values

are set at 15 TWh/year before adjustment. These values are then iteratively adjusted to match the total national industrial hydrogen demand given in EHB (2021b). Where the sum of regional values falls below the national total, values are shifted towards the upper bounds of their ranges or additional demand is assigned to the highest demand scale. Where the sum exceeds the national total, values are shifted towards the lower bounds. This results in a spatially distributed hydrogen demand consistent with both the regional pattern and the national totals from EHB (2021b). Expected hydrogen demand for heating and transport is not included in this study, as this demand is distributed across all areas and not concentrated at the high-demand industrial nodes connected to the backbone.

Hydrogen demand profiles are taken from the ENTSO-E TYNDP 2024 dataset (ENTSO-E & ENTSG, 2024), consistent with the electricity demand profiles. National hourly profiles in the NT scenario are used and scaled to the regional demand values derived from EHB (2021b).

Neither electricity nor hydrogen is assigned an explicit market or export price. Demand must be met within the system, so the value of each energy carrier is represented implicitly through the requirement to satisfy demand rather than through an external price.

4.3.5. Profiles

Generation and demand profiles are based on weather year 2009 where available, ensuring consistency across carriers and asset types, with run-of-river hydro the one exception described below. The electricity and hydrogen demand profiles are taken from the ENTSO-E TYNDP 2024 dataset (ENTSO-E & ENTSG, 2024), as described in Section 4.3.4.

Normalised hourly availability profiles for onshore wind (Staffell & Pfenninger, 2016) and solar PV (Pfenninger & Staffell, 2016) are downloaded from Renewables.ninja at NUTS-2 region level. For NUTS regions that were aggregated from multiple sub-regions, the profile is taken as the average of the constituent regions which slightly smooths intermittency compared to individual region profiles. Norway uses an older NUTS classification in the dataset, so profiles for the previous regional boundaries are averaged to match the current NUTS regions.

Offshore wind profiles are downloaded from Renewables.ninja (Staffell & Pfenninger, 2016) at each of the thirteen hub locations. Profiles are generated assuming a Vestas V164 9.5 MW turbine with a hub height of 110 metres, which is representative of modern large-scale offshore wind turbines and also used in the research of Calado et al. (2024). A nominal capacity of 1 kW is used to obtain a normalised output fraction in the range $[0,1]$, which is then applied to the hub capacities defined in Section 4.2.1.

Run-of-river hydro profiles are derived from hourly generation data downloaded from the ENTSO-E Transparency Platform (ENTSO-E, 2026), divided by total installed capacity per country to obtain normalised availability profiles. Since 2009 generation data was not available, 2019 data is used instead. Given the minor contribution of run-of-river hydro to total generation in the North Sea region, this approximation is not expected to significantly affect results.

The same normalised profiles are used across all milestone years. Only the installed capacities and peak demand values change between 2030, 2040, and 2050, scaling the profiles to the appropriate absolute levels for each year.

Reservoir hydro is not assigned an hourly availability profile. Instead, an annual energy limit is imposed for each plant, constraining total annual generation to match historical national production levels from 2019 (ENTSO-E, 2026). National production totals are distributed proportionally across reservoir hydro plants within each country based on installed capacity.

4.4. Clustering into representative periods

Optimising the full year at hourly resolution across two milestone years and four scenarios is computationally intractable. Reducing temporal resolution to keep the problem solvable is a recognised trade-off in large-scale ESOMs (Fattahi et al., 2021). To reduce the problem size while preserving the temporal variability of demand and renewable availability, the full year is approximated by a set of representative periods using TulipaClustering.jl, a Julia package developed as part of the Tulipa Energy Model (Soares Siqueira et al., 2026). The year is divided into weekly periods of 168 hours, clustered into four representative weeks. The final 24 hours of the year are trimmed so that the year divides into

52 whole weeks of 168 hours, giving 8736 hours in total. Weekly periods are chosen over daily periods so that the representative periods capture not only daily cycles but also multi-day patterns in wind availability and demand, which are relevant for storage operation and hydrogen buffering, consistent with Gea-Bermúdez et al. (2023) and Bødal et al. (2024). Four representative weeks were selected as the maximum temporal resolution for which all four scenarios were capable of reaching an optimal solution within an 8-hour limit when optimising with Gurobi 12.0.0 on a 32-core allocation (Intel Xeon Gold 6248R @ 3.00GHz, 125 GB RAM) on the TU DelftBlue supercomputer (Delft High Performance Computing Centre (DHPC), 2026). Unlike k-medoids (used by Hardy et al. (2023)) or k-means, which represent each cluster by a single member period or an average, the convex hull method selects more extreme representative periods that lie on the boundary of the data. Combined with blended convex weights, each original week is then expressed as a weighted combination of these representative periods. This better preserves periods that are likely to be constraint-binding in the optimisation, such as low-wind or peak-demand weeks, which is important because energy systems must be designed to remain reliable under these challenging conditions. Each representative period is assigned a weight reflecting how many weeks of the full year it represents, which scales operational costs and energy balances in the objective function and constraints accordingly (Neustroev et al., 2025).

4.5. Network representations and scenario design

This section describes how the four scenarios are constructed and solved. The overall workflow is shown in Figure 4.5. Data preparation builds the three core inputs of the model: offshore hub locations from weighted k-means clustering, the aggregated electricity network from `ElectricityNetworkReduction.jl`, and four representative weeks from temporal clustering. These feed into a two-step optimisation. The first step sizes the networks, producing a single fixed set of capacities and reactances. The second step solves the four scenarios on this common network, each producing the evaluation metrics used to answer the research question. The remainder of this section explains the two-step approach, the network representations that define the scenario axes, and the resulting scenario design.

4.5.1. Two-step optimisation approach

Several modelling choices apply uniformly across all scenarios. The simple investment method is used because cost and availability assumptions are defined uniformly per milestone year rather than per commission year, meaning vintage-specific tracking would add computational complexity without adding meaningful information. The model is deterministic with perfect foresight, as the scenario design captures the key source of variation rather than parametric uncertainty. All investment variables are continuous, keeping the formulation as a pure LP, which is sufficient given that individual unit-level decisions are not the focus of this study. A social discount rate of 5% is applied uniformly across all assets and flows. The technology-specific discount rate is set equal to the social rate for all technologies, and 2030 is used as the discount reference year. Electricity and hydrogen transmission connections are assigned a technical and economic lifetime of 30 years (Hystories, 2022).

The transmission dataset from Xiong et al. (2025) represents the current high-voltage grid, not the expanded future network. Detailed network capacities for future milestone years are therefore not available at the spatial resolution used in this study. The electricity grid and hydrogen backbone therefore require investment decisions to determine how much transmission and pipeline capacity is needed in each milestone year. However, these capacity investments cannot be optimised simultaneously with the DC-OPF formulation in Tulipa. The DC-OPF constraint fixes the relationship between flows, reactances, and voltage angles for a given network topology. If line capacities are themselves decision variables, the reactance of each line changes with investment, meaning the power flow physics would depend on the investment outcome. This circular dependency cannot be represented within a single linear optimisation, which is a reason most studies do not co-optimize network capacity with the flow physics. Glaum et al. (2024) specifically highlights that it would transform the model into an MILP, intractable for these North Sea area scopes. To keep it an LP problem, Hagspiel et al. (2014) demonstrate an approach where flow distribution factors are recomputed after each change in line capacity until the network configuration and its flow physics are mutually consistent. Their iterative method requires multiple sequential solves and would produce a network co-optimised with the physics of each individual scenario run. Since this study aims to isolate the effect of modelling representations across four scenarios, a common network basis is essential.

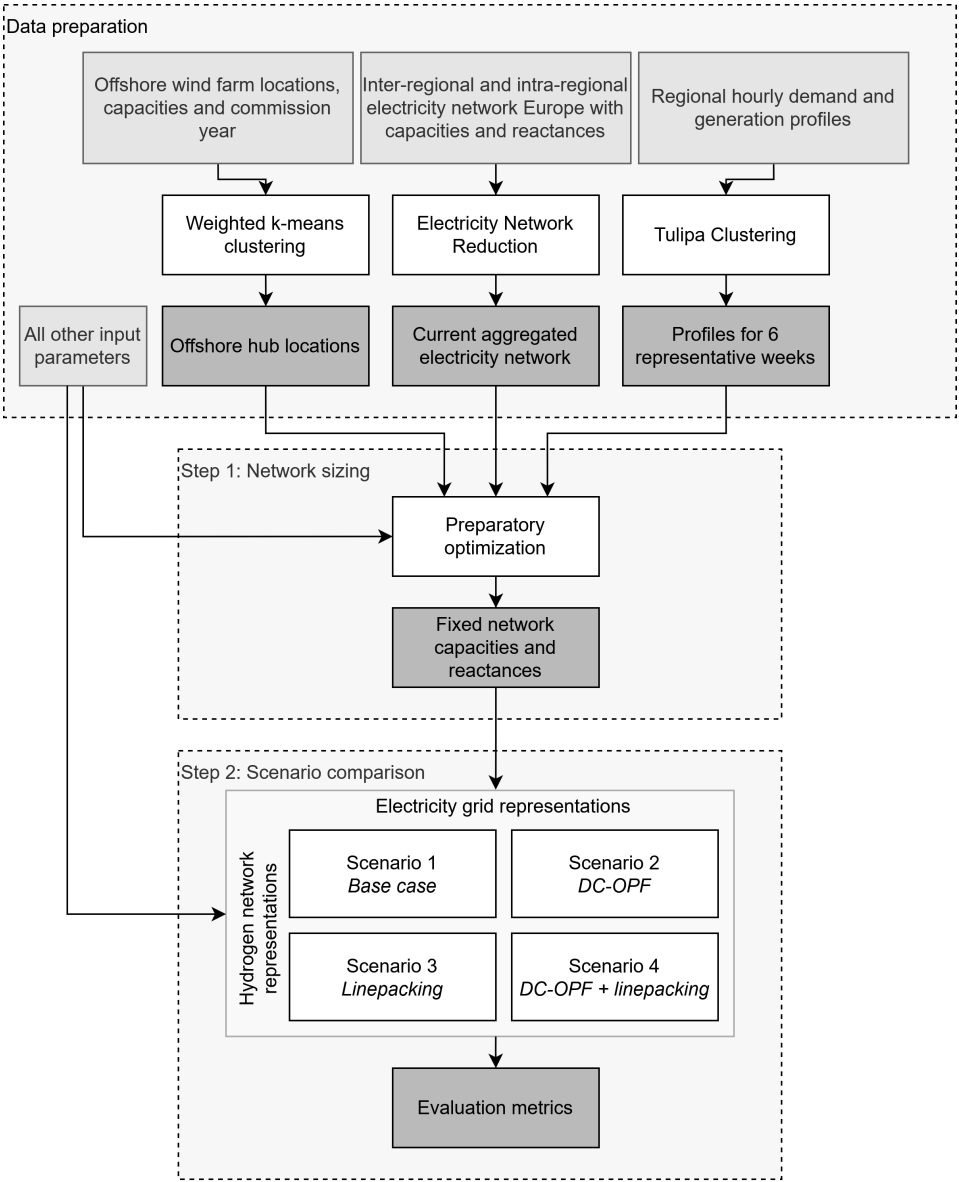


Figure 4.5: Modelling workflow. Data preparation derives offshore hub locations, the aggregated electricity network, and four representative weeks. Step 1 sizes the networks through a preparatory optimisation, producing fixed capacities and reactances. Step 2 solves the four scenarios on this common network to produce the evaluation metrics.

A two-step approach therefore better serves the research design and keeps the comparison computationally tractable. In the first step, a preparatory optimisation is run in which electricity and hydrogen network capacities are investable, using the transport flow formulation for both carriers. The offshore network is also investable in Step 1, ensuring that the onshore grid is sized to realistically accommodate future offshore wind connections and energy exports. This step determines cost-optimal grid and pipeline capacities for each milestone year. In the second step, the onshore electricity and hydrogen network capacities are fixed as inputs, and the four scenarios are run with these network capacities held constant. The offshore network remains investable across all four scenarios, allowing the cost-optimal configuration of offshore infrastructure and electrolyser locations to be determined as part of each scenario comparison. This allows the DC-OPF physics to be applied to a fixed onshore network in the relevant scenarios, while ensuring that all four scenarios are compared on the same underlying network.

Before the second step, the reactances of all electricity transmission connections are updated to reflect the capacities determined in the first step. When transmission capacity is expanded by adding parallel lines, the combined reactance of a corridor decreases in proportion to the capacity increase. This gives the following scaling relationship:

$$p_{f,y}^{\text{reactance new}} = p_{f,y}^{\text{reactance orig}} \cdot \frac{p_{f,y}^{\text{cap orig}}}{p_{f,y}^{\text{cap new}}} \quad (4.1)$$

where $p_{f,y}^{\text{reactance orig}}$ and $p_{f,y}^{\text{cap orig}}$ are the original reactance and capacity from the initial network, and $p_{f,y}^{\text{cap new}}$ is the capacity determined in the first step. This one-time recalculation ensures that the DC-OPF constraints in Step 2 reflect the physical properties of the expanded network rather than those of the original grid.

A consequence of this approach is that the first-step network capacities are determined without DC-OPF and linepacking physics, so they represent a cost-optimal but physically simplified network expansion. This is a deliberate choice, not only a computational one. Fixing the network is what makes the scenario comparison possible: if each scenario optimised its own grid, the differences between them could reflect the network rather than the representation being tested. It also means that any congestion the DC-OPF physics produce in the scenario runs is measured on a grid not built for those flows. A grid co-optimised with the DC-OPF physics would relieve much of that congestion, because it would be sized to accommodate the constrained flows. Studying congestion on a fixed network is the intended purpose of the design, not an artefact to be removed: it is how the model reveals what the network representation implies for a given network. The resulting capacities should be read as a consistent common basis for comparing the scenarios, not as a fully physically optimal grid expansion.

Because network capacities are fixed in the scenario runs, situations may arise where demand at a node cannot be met due to generation or transmission limits. To avoid model infeasibility, a dummy producer is connected with each demand node, supplying energy at a high operational cost. The cost is differentiated to reflect that the modelled region is not isolated in reality. Nodes that have real connections to countries outside the modelled area use a lower cost of 999 EUR/MWh, representing electricity import from those neighbouring systems, which the model can then distribute onward where the network allows. Remaining internal nodes use a higher cost of 9999 EUR/MWh, representing genuine unmet demand that cannot be resolved even through import. The use of these dummy producers in the results indicates where the fixed network is insufficient to meet demand, and is reported and interpreted accordingly. The influence of these dummy producers on the results is limited. They are not activated in 2030 in any scenario, and in 2040 they supply about 0.2% of total energy. Whether this activation distorts the electrolyser siting result is examined in Section 7.1.

4.5.2. Scenario 1: Transport model

In the base case, both the electricity grid and the hydrogen backbone are represented using the standard transport flow representation. Energy flows on each connection are optimised freely by the solver up to the capacity bound defined for that connection, without any constraint on the physical path power or gas takes through the network. For both electricity and hydrogen, this means flows between any two

connected nodes are unconstrained beyond their line or pipeline capacity limits, regardless of network topology, line reactances, or pressure dynamics.

This representation is a widely used and computationally efficient approach in large-scale energy system models, and serves as the reference against which the more detailed representations in this study are evaluated. All assets and flows operate at hourly resolution, meaning electricity and hydrogen supply and demand must balance at every node at every hour in each representative period with no flexibility to shift production or consumption within a longer time window.

4.5.3. Scenario 2: DC optimal power flow

In the second scenario, the transport flow formulation for the electricity network is constrained by the DC-OPF formula described in Section 3.3.3. Rather than freely routing power up to line capacity limits, flows on AC electricity transmission lines are now physically determined by the voltage phase angle differences between connected nodes and the reactance of each line. This enforces Kirchhoff's laws across the entire network, meaning power flows distribute across parallel paths according to network physics rather than cost optimisation alone. Also consistent with Löhr et al. (2023), reactive power is not included in this model.

The key consequence is that power flowing between two nodes partially loads transmission lines in other parts of the network, even lines not directly on the cheapest route between them. This can cause lines to become congested that have spare capacity under the transport model, because physics forces power through them regardless of cost. Conversely, lines that carry heavy flows under the transport model may be less utilised under DC-OPF, as the physics redistribute flows across parallel paths. As a result, the power that can physically be delivered to or from a node depends not only on the direct connection capacity but on the broader network topology.

This has direct implications on the optimal location of electrolyzers. An offshore hub or onshore node that appears to be well connected and uncongested under the transport model may face binding electricity grid constraints under DC-OPF. When such constraints become binding, the shadow price of the balance constraint at that node increases, reflecting a higher marginal cost of electricity at that location. This shifts the cost-optimal location for electrolyser investment away from congested nodes towards nodes where electricity can be delivered at lower marginal cost. DC-OPF therefore introduces locational differences in electricity costs that Scenario 1 cannot capture, which is expected to influence the cost-optimal location of hydrogen production.

4.5.4. Scenario 3: Linepacking

Linepacking refers to the ability of a pressurised gas pipeline to temporarily store gas by varying its internal pressure, providing short-term operational flexibility between in- and outflow of the hydrogen network. In most large-scale energy system optimisation models, the physical dynamics of linepacking are computationally complicated to model explicitly, and gas networks are typically represented as static transport systems that assume immediate delivery. This means that hydrogen supply and demand must balance at every node at every hour, with no flexibility within pipelines to decouple electrolyser production from downstream demand within a short time window.

In this study, linepacking flexibility is approximated by exploiting Tulipa's flexible temporal resolution feature (Gao et al., 2025). All hydrogen flows are assigned four-hour timestep blocks while electricity assets retain hourly resolution. This temporal differentiation is consistent with established practice in integrated energy system models where gaseous networks are operated at lower resolution than electricity networks. While Sánchez Diéguez et al. (2022) and Martínez-Gordón et al. (2022) use a daily resolution for gaseous networks in general (and hourly for electricity), this research uses a four-hour block length. Sargent and Sargent (2025) define a linepack flexibility metric in hours, calculated as the useful stored energy in a pipeline divided by the designed power flow. For a 139 km hydrogen transmission example carrying 21.7 GW, they calculate a flexibility of 2.74 hours. Hydrogen provides only 33 to 42% of the linepack capability of natural gas (in this example 10.37 hours) over practical pressure ranges (Sargent & Sargent, 2025). This places hydrogen pipeline buffering capacity in the 3 to 5 hour range for typical backbone segments. Ameli et al. (2025) further classify linepacking as a source of intra-day flexibility, confirming it operates on hourly timescales. A four-hour block therefore falls within the plausible buffering window while remaining a modelling approximation rather than a

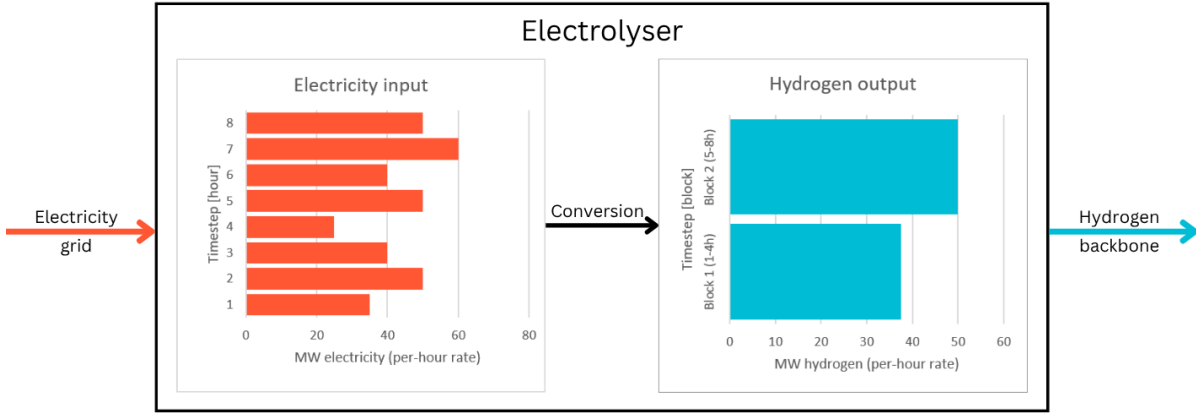


Figure 4.6: Temporal resolution at an electrolyser in the linepacking scenario. Electricity is consumed hourly with varying dispatch, while hydrogen is delivered at a constant rate across each four-hour block. Bar area represents energy, so the electricity consumed over the block times efficiency equals the hydrogen produced.

precisely calculated value.

The practical effect on model behaviour is as follows. At an electrolyser node, electricity flows in at hourly resolution and the conversion balance is enforced across the full four-hour block: the sum of hourly electricity inputs multiplied by efficiency must equal the total hydrogen output for that block. The electrolyser can therefore concentrate electricity consumption in low-price hours within the block while delivering a constant average hydrogen flow rate across the window. At a hydrogen demand node, the hourly demand profile is automatically aggregated as the mean across each four-hour block, so the pipeline flow must satisfy the average demand rate over the window rather than an instantaneous hourly value. At a conversion asset where hydrogen is converted to electricity the opposite applies: hydrogen is consumed at a constant four-hour rate while electricity output is free to vary hour by hour within capacity limits, as long as total electricity produced across the block is consistent with hydrogen consumed. Together, these behaviours allow these assets to exploit intra-block electricity price variability and decouple hydrogen production from instantaneous demand. This imitates the most important characteristics of linepacking without requiring explicit pressure-flow dynamics.

Figure 4.6 illustrates the practical effect of this representation at an electrolyser node. The electricity input varies across the eight hourly timesteps in response to price differences, while the hydrogen output flows at four-hour block resolution. The bar areas represent energy: the sum of electricity consumed over the four hours, multiplied by the electrolyser efficiency (assumed 1 in this figure), equals the hydrogen delivered at the constant block rate. This decoupling of hourly electricity dispatch from the four-hour hydrogen delivery rate is what gives the hydrogen assets their intra-block flexibility, and is the core mechanism that linepacking introduces relative to the base case.

4.5.5. Scenario 4: DC-OPF and linepacking

The fourth scenario activates both representations simultaneously. The electricity network is governed by DC-OPF constraints while hydrogen assets and pipeline flows operate at four-hour temporal resolution. This combination allows the model to capture the interaction between physical electricity network constraints and hydrogen pipeline flexibility within a single optimisation.

Under DC-OPF, the implicit marginal cost of electricity varies by location depending on network congestion and topology. The linepacking representation then allows electrolysers to exploit variation in these location-specific costs within each four-hour block, concentrating production in hours when electricity is cheapest. The two representations therefore interact through the conversion assets connecting both networks: DC-OPF shapes which locations face lower electricity costs, while linepacking determines how much temporal flexibility is available to exploit those cost differences.

4.6. Conclusion on case study

This chapter applied the modelling approach to the North Sea energy system. It defined the eight-country study area at NUTS resolution, the aggregation to the offshore hub network, the onshore electricity grid, and the hydrogen backbone from independent data sources. The generation and storage fleets are fixed, so that investment responds only through the conversion assets and the offshore network. The full year is represented by four convex-hull clustered weeks. A two-step design sizes the networks once under the transport formulation and then holds them fixed, so that any difference between the four scenarios comes from the network representation and not from the underlying capacities. On this common basis the four scenarios vary the electricity representation between transport and DC-OPF and the hydrogen representation between no linepacking and a four-hour approximation. The next chapter reports and compares their results.

5

Results

5.1. Preparatory optimisation for fixed network capacities

Step 1 runs a single optimisation with investable electricity and hydrogen networks, using the transport flow formulation. It produces cost-optimal network capacities for 2030 and 2040. These capacities are fixed and used as the same network in all four scenario runs. This is what makes the scenarios comparable: with an identical grid, any difference in nodal prices, line duals, or objective values comes from the network representation and not from a different network.

Each hub represents all OWFs in its cluster, and its power has to reach shore to be used. Distance is the main driver of where it lands. Offshore cables are more expensive per kilometre than onshore reinforcement, so a hub tends to connect to a nearby onshore region that can take its power, with the onshore grid distributing it further from there. Inter-hub connections appear where several hubs can be routed to shore through the same connection.

Offshore electricity and hydrogen connections, and all investable asset capacity, are excluded from this fixed network. They start from zero and stay investable in every scenario, because electrolyser location and offshore connection capacity are the outcomes this study compares. The onshore grid, by contrast, must be fixed in every scenario, including the base case. A separate optimisation is needed because no single scenario's own network is neutral: each scenario invests differently offshore, so the onshore grid it would produce is shaped by that scenario. The preparatory optimisation instead produces one onshore network that all scenarios share. S1 is therefore the common reference for the comparison. It applies the transport model to the network that the preparatory run found optimal, so it adds no physics beyond the preparatory run itself. S2, S3, and S4 are each read as a departure from S1, caused by the representation each one adds.

5.1.1. Offshore electricity network

These offshore investments are not carried into the scenarios, but they determine the onshore capacities that are. Each large offshore landing forces the onshore grid to carry that power inland, so the offshore pattern explains the onshore capacities in Section 5.1.2. Figures 5.1 and 5.2 show that almost all onshore increases follow the routing of offshore wind to the mainland demand regions.

By 2030, the model invested in direct connections from multiple hubs to shore. The two largest serve the Netherlands: Hub 5 (H5) in the central North Sea connected to NL11 in the northern Netherlands with 18.4 GW, and Hub 2 (H2), west of the Netherlands, connected to NL33 with 29.5 GW. These central North Sea hubs collect the largest amount of offshore wind, and they lie close to the Dutch and German demand centres, so connecting them directly to the Netherlands is the cheapest way to bring that power to shore. Hub 9 (H9), positioned east of the UK, delivered 20.2 GW to UKC2 in northeast England. Hub 3 (H3) connected to UKF3 with 9.9 GW, and Hub 1 (H1) linked to BE25 at the Belgian coast with 9.4 GW. Hub 12 (H12) connected to UKM6 in Scotland with 9.6 GW and Hub 7 (H7) to DEF0 with 3.8 GW. Hub 8 (H8) connected to DK04 with 1.5 GW. Furthermore, an inter-hub offshore grid began to emerge. H2 and H3 each connected to H4 with 5.3 GW links. H2 also connected to H3 with

a 2.2 GW line and H9 connected to H11 with a 5 GW line. Several smaller inter-hub and hub-to-shore connections also formed, which are shown in Figure 5.1.

By 2040, shore connections expanded further and the inter-hub network grew substantially. H5 to NL11 grew to 56.8 GW, making it the largest single transmission corridor in the system. This is roughly twice the capacity of the largest connection in the initial aggregated network, reflecting how much offshore wind power the model concentrates on this single corridor. H3 to UKF3 reached 30.1 GW, H8 to DK04 expanded to 11.5 GW and H13 connected to NO09 with 3.7 GW. In the offshore grid, the H2-H3-H4 cluster extended with two new connections: H4 and H5 connected to H6 with around 17 GW each. H3 to H4 grew to 22.7 GW, and H9 to H11 grew to 8.3 GW. H1 also connected to UKJ4 with 6.3 GW in 2040. H7 connected to DK03 with 4.7 GW. This and the other connections are visualised in Figure 5.2.

5.1.2. Onshore electricity network

The offshore landing capacities directly determine the scale of onshore investment. The Netherlands functions as the central electricity transit hub of the preparatory network, responding in two phases. In 2030, the 29.5 GW landing at NL33 from H2 drove NL33 to NL41 to expand to 21.7 GW to distribute power southward. By 2040, H5's connection to NL11 grew to 56.8 GW, requiring NL11 to NL21 to expand to 28.5 GW. Three corridors carry power onward into Germany: DE94 to NL11 reached 25.9 GW, DEA2 to NL42 reached 16.6 GW, and DEA3 to NL21 expanded to 19.2 GW by 2040.

In the UK, H9's 20.2 GW landing at UKC2 in 2030 required UKC1 to UKC2 and UKC1 to UKE2 to expand to 18.6 GW and 18.2 GW respectively to carry power southward. In Scotland, H12's 9.6 GW landing at UKM6 in 2030 drove UKM6 to UKM7 to expand to 4.1 GW, reaching 7.2 GW by 2040. The 30.1 GW arriving at UKF3 from H3 by 2040 required UKF1 to UKF3 to expand to 17.7 GW, creating an extra corridor to transport electricity to inland regions.

The Scandinavian corridor expanded across both milestone years. DK03 to DK04 grew from 5.4 GW to 13.5 GW by 2030 and reached 22.0 GW by 2040. The DC interconnector DK04 to NO09 expanded to 11.5 GW by 2030, with minimal further investment by 2040. The DC interconnector UKJ4 to FRE1 grew to 9.8 GW by 2030 and 15.7 GW by 2040, a corridor transferring power between the UK and continental European demand. Other DC connections received modest expansions by 2040: UKJ4 to BE25 reached 2.5 GW, DK03 to DK02 reached 2.3 GW, and UKN0 to UKM9 reached 1.9 GW.

The resulting fixed onshore network is shown in Figure 5.2. Three Belgian connections between BE10, BE24, BE31, and BE32 with artificially high capacity values resulting from the manual connectivity are excluded from the investment map.

In each case the onshore expansion follows the offshore landing: capacity grows first on the corridors leaving the landing node, then further inland where the power has to continue toward demand.

5.1.3. Hydrogen backbone

The hydrogen backbone was initialised at 10 GW per segment across the full EHB network, under the assumption that the planned backbone is available from 2030. This base capacity is sufficient almost everywhere. Four onshore segments required additional capacity, all in 2040: DEF0 to DE93 reached 19.8 GW and DEF0 to DK03 reached 14.8 GW, indicating a hydrogen flow corridor between Germany and Denmark. Two connections in the northwest England to Scotland corridor received additions of only 0.3%. A small offshore hydrogen network emerged in 2040: Hub 8 developed a pipeline to DK04 (5.5 GW) with an inter-hub connection to H10 (5.5 GW), and Hub 12 connected to both H13 and UKM5 with 2.7 GW each. All other backbone segments remained at 10 GW through both milestone years. The resulting hydrogen network is shown in Figure 5.3. These additions sit near the largest onshore electrolyser locations of the preparatory run rather than near the offshore landings, so the hydrogen network expands where hydrogen is produced, not where it comes ashore.

Taken together, the two networks expand differently. Electricity investment runs to tens of GW on the corridors where offshore wind distributes to inner regions, while hydrogen backbone investment is confined to single regional bottlenecks in northern Germany and the UK. This network was sized alongside the electrolyser locations chosen in the preparatory run, and those locations are not carried forward into the scenario runs. Where a scenario places electrolyzers differently, the fixed network may be over- or under-dimensioned for those locations. Furthermore, a network that is cost-optimal

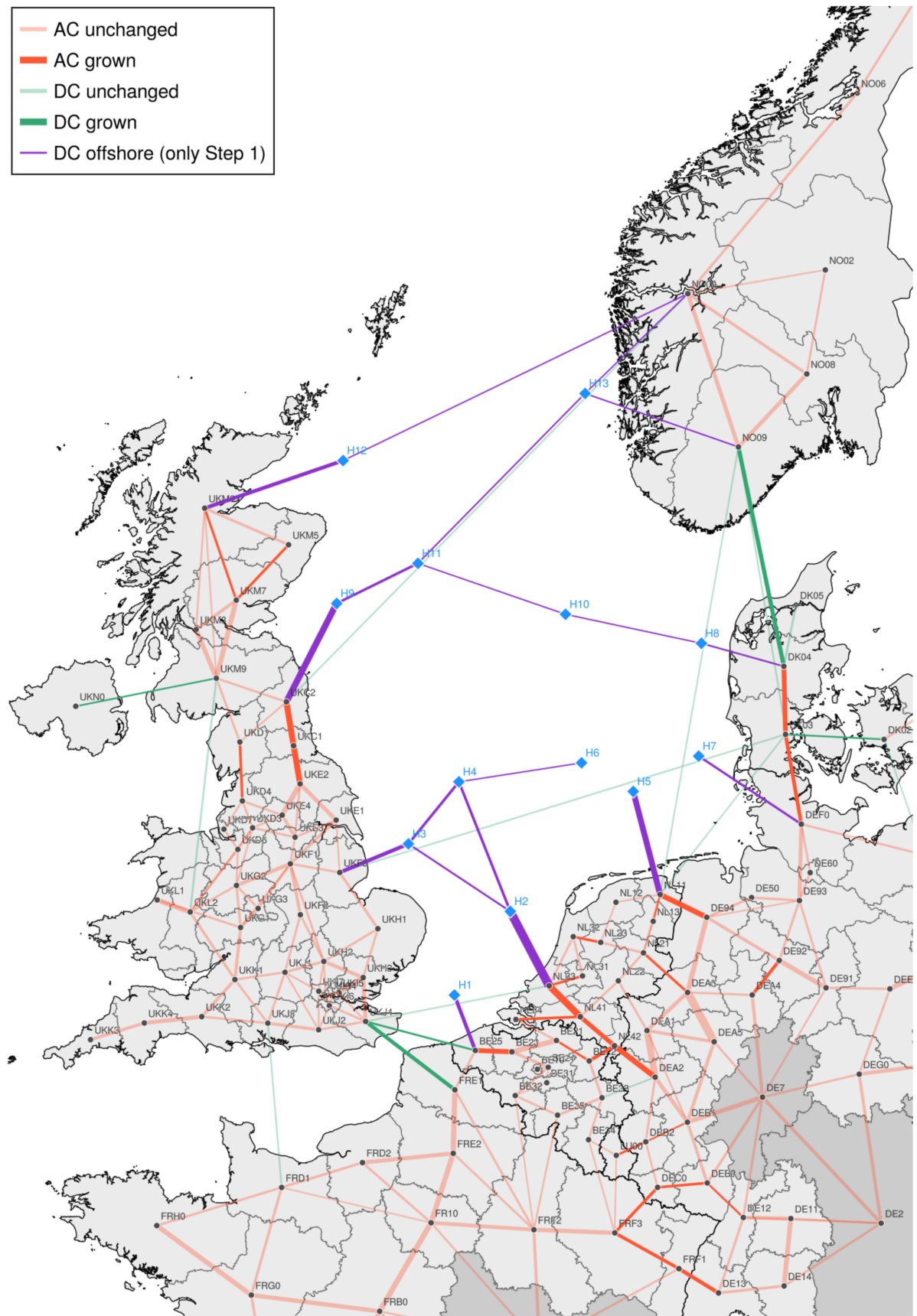


Figure 5.1: Preparatory optimisation network capacities for 2030. Purple lines are offshore connections. In the scenario runs they are reset to zero and optimised again as investment decisions. Coral lines are onshore AC, green lines onshore DC. Line thickness shows capacity. Opaque lines received no capacity increase; lines absent from the figure did not change. The thick offshore landings and the onshore corridors growing inland from the coast show how offshore wind drives the onshore capacity increases.

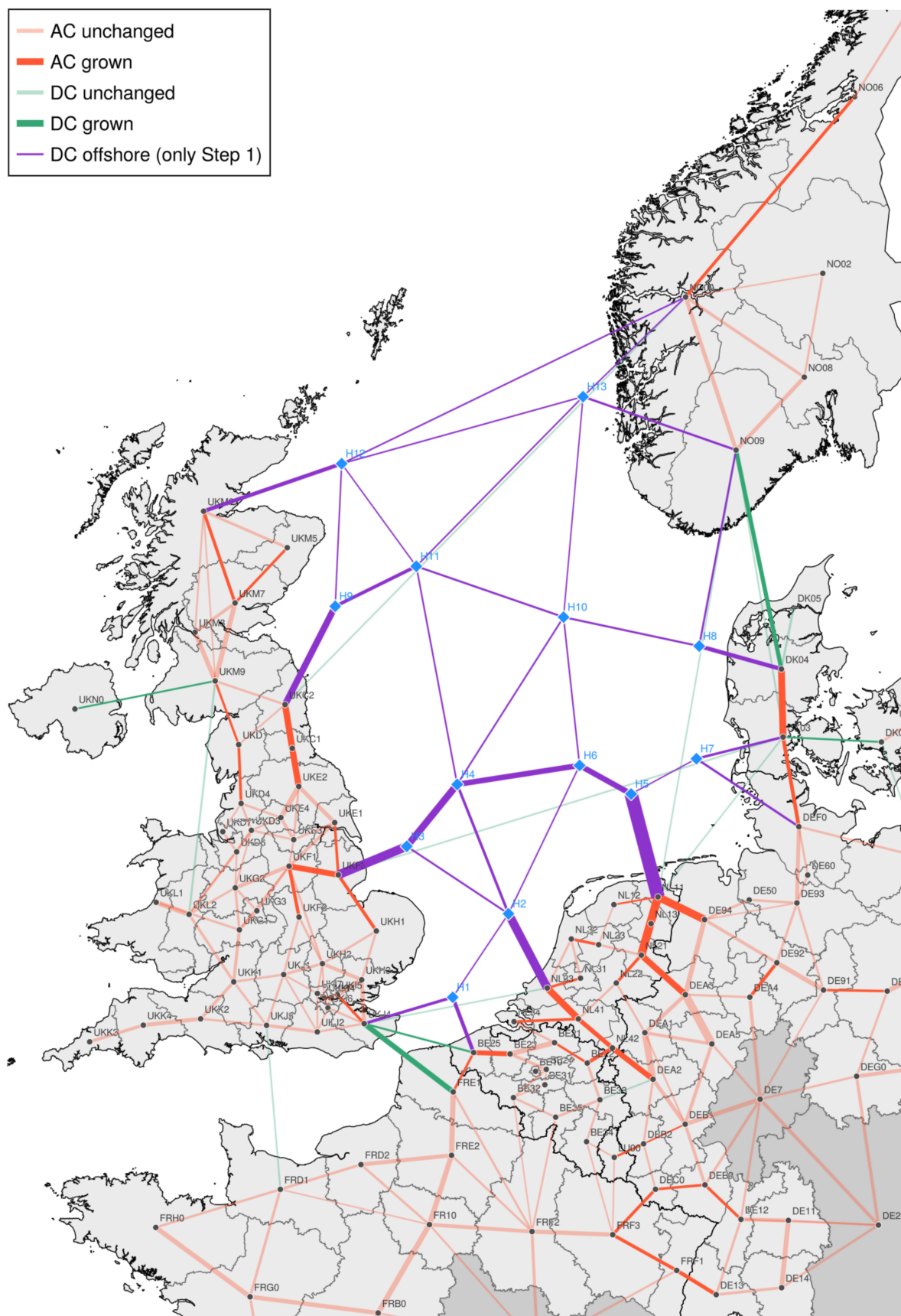


Figure 5.2: Preparatory optimisation network capacities for 2040. Purple lines are offshore connections. In the scenario runs they are reset to zero and optimised again as investment decisions. Coral lines are onshore AC, green lines onshore DC. Line thickness shows capacity. Opaque lines received no capacity increase; lines absent from the figure did not change. The thick offshore landings and the onshore corridors growing inland from the coast show how offshore wind drives the onshore capacity increases.

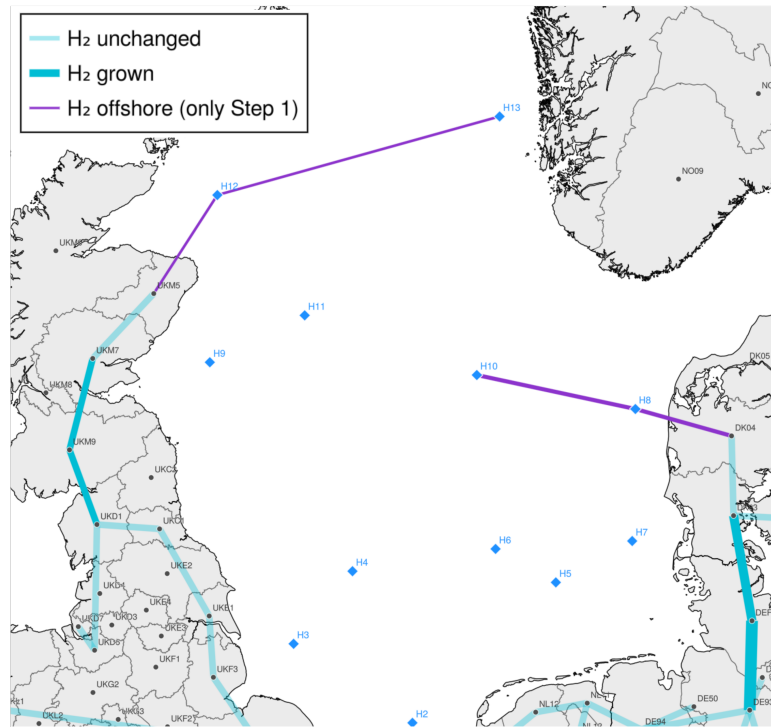


Figure 5.3: Preparatory optimisation hydrogen backbone capacities for 2040. Purple lines are offshore connections. In the scenario runs they are reset to zero and optimised again as investment decisions. Line thickness shows capacity. Opaque lines received no capacity increase; the backbone starts at 10 GW everywhere. The additions concentrate on the Germany-to-Denmark corridor, while the rest of the backbone stays at its initial 10 GW.

under the transport formulation can still bind under the other network representations. Dummy producer activations in the scenario results show where either of these becomes limiting.

5.2. Electrolyser investment location

Where hydrogen production is built, onshore or offshore, is the central outcome of this study. This section reports the cost-optimal electrolyser locations under the four scenarios: S1 the transport flow base case, S2 with DC-OPF included, S3 with linepacking included, and S4 with both. It compares them on total capacity, on the onshore-offshore distribution, and on which specific nodes are chosen, in 2030 and 2040. The mechanism behind these differences, the locational price of electricity and the network congestion that creates it, is established in Sections 5.4 and 5.5. This section covers the siting outcome, and for electrolyzers only. The model also invests in hydrogen-to-power conversion assets (H_2 -CCGT, hydrogen gas turbines, fuel cells). Their investment cost is reported in Section 5.3.

The mechanism behind the differences reported here is locational cost. A network representation determines whether electricity has large differences in electricity prices between nodes, and an electrolyser is cheapest where the electricity it consumes is cheapest. DC-OPF enforces flow physics resulting in congestion, so cheap northern and offshore power cannot always reach interior demand, and the nodes separate in cost. The transport model prices nodes almost alike, so less separation exists. This section reports where capacity is built. Sections 5.4 and 5.5 establish the prices and the binding lines that produce it.

Capacity by scenario

Figure 5.4 shows the cost-optimal electrolyser locations for each scenario in a 2x2 grid, Table 5.1 lists the largest investments by location, and Figure 5.5 compares total onshore and offshore capacity across scenarios and years. Two features stand out in the map. The onshore-offshore split is similar within each row and differs between them: the transport scenarios (S1, S3, left) place almost all capacity onshore, while the DC-OPF scenarios (S2, S4, right) place more and larger capacity offshore. And

the two linepacking pairs are visually close: S1 resembles S3 and S2 resembles S4, showing that linepacking barely moves where capacity is built.

Across all scenarios electrolyser investment is predominantly onshore. In the transport scenarios all 2030 investment is onshore, and offshore capacity is limited to Hub 10 and Hub 13 in 2040, reaching at most 12.5% of cumulative capacity. The DC-OPF scenario invests offshore already in 2030 and reaches a higher 2040 offshore share of 16.4% across four hubs. Total capacity also differs: S2 reaches 75.6 GW by 2040, about 15% above S1 (65.7 GW), and S4 reaches 74.6 GW, about 17% above S3 (63.9 GW).

Three things are visible even before the price mechanism is established. Offshore capacity stays confined to a few hubs in every scenario, and it appears earlier and at more hubs under DC-OPF. This happens even though offshore electrolyzers are more expensive than onshore (Section 5.3). For that premium to be paid, DC-OPF has to make those hubs relatively cheap enough on the electricity side to outweigh it. Yet more than four fifths of capacity is onshore in every scenario and year. A third pattern is visible onshore. The DC-OPF scenarios drop five interior German nodes that the transport scenarios select, the largest being DE2 and DEE0, while placing more capacity at the coastal and northern nodes. On the map this shows as circles disappearing from central and eastern Germany between the left and right columns. Why DC-OPF pushes capacity offshore and away from these interior nodes, and why onshore still keeps the higher share, is examined with the price and congestion results in Sections 5.4 and 5.5. Linepacking, by contrast, leaves the distribution almost unchanged, because it acts on how electrolyzers operate within the day rather than on where electricity is cheapest to convert (Section 5.6).

Table 5.1: Electrolyser investments by location and scenario. The 2030 block shows the investments in that milestone year. The 2040 block shows total available capacity by 2040 (2030 investments plus 2040 additions). The table shows locations with at least 1 GW (2030 block) in any scenario or 2.5 GW (2040 block) in any scenario; system totals include all locations.

<i>2030 total capacity (GW)</i>					<i>2040 total capacity (GW)</i>				
Location	S1	S2	S3	S4	Location	S1	S2	S3	S4
UKM7	8.1	4.5	7.3	4.3	DK03	10.6	12.8	10.9	11.9
DK03	6.9	4.7	3.8	3.3	DE94	10.4	11.4	10.0	11.4
DE94	–	3.5	–	3.2	UKM7	8.1	4.5	7.6	4.3
DEF0	–	1.3	1.7	2.1	NL33	3.8	6.8	2.9	7.3
DEB3	–	1.9	–	1.8	FRK	5.8	5.7	3.3	5.3
DE93	1.4	0.5	1.0	0.6	DEF0	5.7	4.1	5.2	4.1
UKC1	–	1.0	–	1.5	FRG0	–	4.9	2.0	2.8
NL41	–	1.3	–	1.1	FRL0	1.9	2.6	2.1	2.3
NL33	0.8	–	1.4	–	DEA5	–	4.2	–	3.9
H12	–	4.0	–	3.4	DE93	3.4	0.5	1.5	0.6
<i>System total</i>	<i>17.2</i>	<i>22.6</i>	<i>16.6</i>	<i>22.2</i>	DEE0	3.8	–	1.9	–
					NL32	1.8	–	2.7	0.5
					DE2	1.6	–	2.8	–
					H10	5.5	4.6	4.6	4.5
					H13	2.7	2.9	2.5	2.8
					H12	–	4.0	–	3.4
					H6	–	1.0	–	2.9
					<i>System total</i>	<i>65.7</i>	<i>75.6</i>	<i>63.9</i>	<i>74.6</i>

Scenario 1: Base case

In 2030, the base case concentrates investment in two locations. UKM7 in the south of Scotland receives 8.1 GW and DK03 in southern Denmark 6.9 GW, together representing 87% of total 2030 capacity of 17.2 GW. Smaller investments appear in DE93 (1.4 GW) and NL33 (0.8 GW). All 2030 investment is onshore.

By 2040, Germany emerges as the dominant electrolyser region. DE94 in north-west Germany receives the largest single investment of any location at 10.4 GW. The DK03 electrolyser capacity grows to 10.6 GW. DEF0 expands to 5.7 GW and DEE0 to 3.8 GW. France attracts investment through FRK (5.8 GW) and FRL0 (1.9 GW). Offshore electrolyzers appear for the first time: H10 receives 5.5 GW

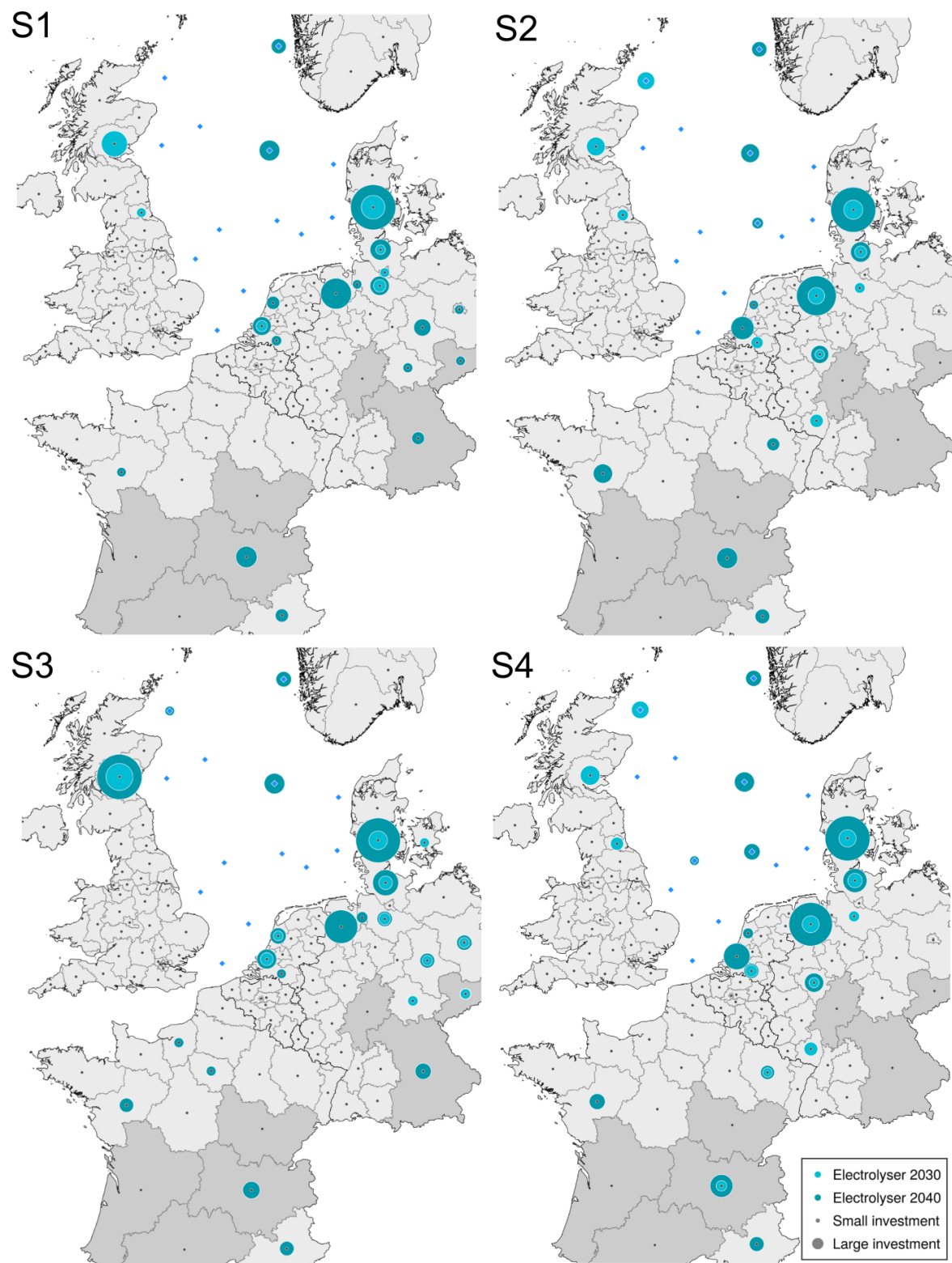


Figure 5.4: Cost-optimal electrolyser investment by location and scenario, in a 2x2 grid: S1 (top left), S2 (top right), S3 (bottom left), S4 (bottom right). Circle sizes scales proportional with invested capacity. Light blue circles show 2030 investment, dark blue circles show 2040 investment. The transport scenarios (left) place almost all capacity onshore, while the DC-OPF scenarios (right) show larger and more offshore investment, and less in the east of Germany.

and H13 2.7 GW, contributing a combined 8.2 GW or 12.5% of total cumulative capacity of 65.7 GW. Scotland receives no further investment in 2040, indicating that UKM7's 2030 attractiveness reflects early offshore wind access rather than a long-run structural advantage.

Scenario 2: DC-OPF

Replacing the free transport assumption with DC-OPF physics changes both the timing and the scale of electrolyser investment relative to S1. Total cumulative capacity by 2040 reaches 75.6 GW, around 15% higher than the base case. The difference is larger in 2030, where total investment of 22.6 GW exceeds S1 by 31%.

In 2030, DK03 and UKM7 remain leading locations but at lower individual capacities than in S1 (4.7 GW and 4.5 GW, against 6.9 GW and 8.1 GW). DE94 emerges already in 2030 with 3.5 GW, a location that attracted no investment that early in S1. The clearest new feature is offshore investment in this milestone year: Hub 12 receives 4.0 GW, accounting for 17.7% of total 2030 capacity. S1 doesn't invest in offshore capacity in 2030, so this shift in early offshore deployment is a new feature under DC-OPF.

By 2040, DK03 grows by a further 8.0 GW to reach 12.8 GW cumulatively, and DE94 grows by 7.9 GW to reach 11.4 GW, both above their S1 equivalents (10.6 GW and 10.4 GW). NL33 reaches 6.8 GW, almost double its 3.8 GW in S1. Offshore capacity is spread across four hubs by 2040: H12 (4.0 GW, built in 2030 and retained), H10 (4.6 GW), H13 (2.9 GW), and H6 (1.0 GW), a location that receives no investment in S1. Combined offshore capacity of 12.4 GW gives an offshore share of 16.4%, compared to 12.5% in S1.

DC-OPF therefore changes three things at once: it builds more capacity in total, brings some of it forward to 2030, and places a larger share offshore. All three point toward the electricity at the onshore nodes having become more expensive, which the price results in Section 5.4 test.

Scenario 3: Linepacking

The linepacking scenario shares the same dominant investment locations as the base case but distributes capacity more broadly in 2030.

In 2030, UKM7 and DK03 remain the two largest nodes at 7.3 GW and 3.8 GW respectively, but DK03 receives substantially less than in the base case (3.8 versus 6.9 GW). The remaining capacity spreads across nine additional onshore locations, including DEF0 (1.7 GW), NL33 (1.4 GW), DE93 (1.0 GW), and four nodes in central and eastern Germany (DEE0, DE40, DEG0, DED) each receiving approximately 0.3 GW. Total 2030 capacity of 16.6 GW is close to the base case. Whether electrolyzers in S3 actually exploit intra-block electricity price variation is examined in Section 5.6.

By 2040, the investment pattern converges with the base case. DE94 remains the largest location at 10.0 GW cumulatively and DK03 reaches 10.9 GW. DEF0 reaches 5.2 GW. The redistribution within smaller nodes is visible but modest: FRK receives 3.3 GW compared to 5.8 GW in the base case, while FRG0 grows to 2.0 GW and DE40 reaches 2.0 GW cumulatively, both negligible in the base case. Offshore capacity is slightly smaller: H10 receives 4.6 GW and H13 2.5 GW, giving an offshore share of 11.2% of total cumulative capacity of 63.9 GW. The total capacity difference between S1 and S3 is less than 3%.

Linepacking therefore redistributes capacity between nodes in both years, most visibly in 2030, but leaves the totals and the onshore-offshore split close to the base case.

Scenario 4: DC-OPF and linepacking

The combined scenario activates DC-OPF and linepacking together. Its investment pattern closely follows the DC-OPF scenario rather than the linepacking scenario, indicating that the electricity network representation dominates the combined effect. Total available capacity reaches 74.6 GW by 2040, around 14% higher than S1 and close to the 75.6 GW of S2.

In 2030, total investment of 22.2 GW exceeds S1 by 29%, almost matching the increase seen under DC-OPF alone. As in S2, DE94 receives early investment (3.2 GW) and offshore capacity appears already in 2030 at Hub 12 (3.4 GW). The dominant onshore locations are again UKM7 (4.3 GW) and DK03 (3.3 GW), both lower than their S1 levels of 8.1 GW and 6.9 GW.

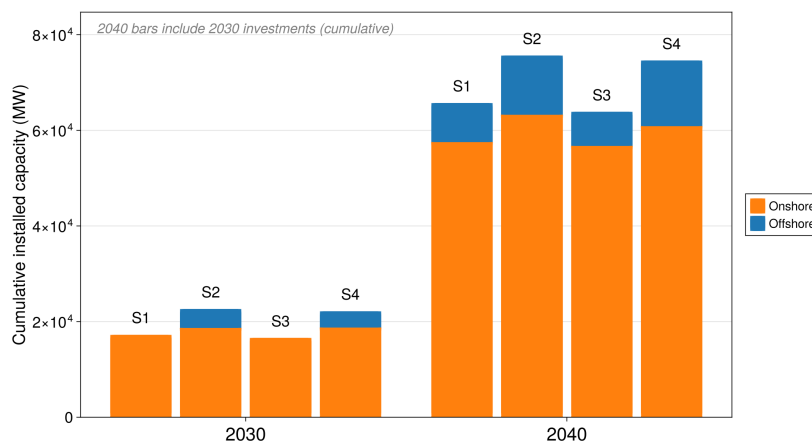


Figure 5.5: Total electrolyser capacity by scenario and milestone year, split into onshore (orange) and offshore (blue). Bars show 2030 and 2040 for each scenario. The DC-OPF scenarios (S2, S4) reach higher totals and larger offshore segments than the transport scenarios (S1, S3), while the two linepacking pairs (S1/S3 and S2/S4) are close, showing linepacking's weak effect on capacity.

By 2040, DK03 reaches 11.9 GW and DE94 11.4 GW, both above their S1 values. NL33 grows to 7.3 GW, the largest NL33 investment of any scenario and almost double its S1 level. The combined scenario produces the highest offshore deployment of all four scenarios: H10 (4.5 GW), H12 (3.4 GW), H13 (2.8 GW), and H6 (2.9 GW) give a combined 13.7 GW, an offshore share of 18.3%. This exceeds both S1 (12.5%) and S2 (16.4%), driven mainly by the larger H6 investment, which reaches 2.9 GW against 1.0 GW in S2.

The combined scenario adds little to DC-OPF alone, which indicates the two representations act on different decisions and do not reinforce each other.

Synthesis

Two effects emerge from the scenario comparison. Linepacking (S3) leaves the long-run 2040 investment geography close to the base case. The same dominant nodes (DE94, DK03, DEF0) account for most 2040 capacity, total capacity differs from S1 by less than 3%, and the offshore share is the lowest of all scenarios at 11.2%. Its main effect is on the 2030 pattern, where it distributes capacity more broadly across nodes and reduces early concentration in DK03.

DC-OPF (S2) has a larger and qualitatively different effect. It raises total electrolyser capacity by around 15%, brings investment forward so that more capacity is built by 2030, and introduces offshore investment already in 2030 at Hub 12. It also raises the 2040 offshore share to 16.4% and selects Hub 6, a location that receives no investment in either transport model scenario.

The combined scenario (S4) follows the DC-OPF pattern closely, confirming that the electricity network representation dominates over linepacking when both are active. S4 produces the highest offshore share of all scenarios at 18.3%. The two representations therefore do not act in the same way: DC-OPF reshapes both the scale and location of electrolyser investment, while linepacking mainly redistributes early investment over regions without changing the long-run pattern. In effect DC-OPF moves conversion toward the wind, building hydrogen production closer to the offshore hubs rather than relying on the network to carry the wind to onshore conversion. It does this even though offshore electrolyzers cost more per MW, so the relative electricity-side advantage DC-OPF gives the hubs outweighs that cost. What that advantage is, and whether it comes from congestion on specific corridors, is examined in Sections 5.4 and 5.5.

The largest onshore nodes are the same in every scenario. DE94, DK03, and DEF0 hold large capacity in all four scenarios and both years. The representation changes how much is built and how much goes offshore, and it drops several interior nodes, but it does not displace the nodes that carry most of the fleet. These nodes stay cheap under every representation, which is why none of the representations rules them out. Section 5.4 sets out the price mechanism behind this.

5.3. System costs

Total discounted system cost across the model horizon ranges from 500.6 billion EUR in S3 to 523.5 billion EUR in S2 (Table 5.2). Around 11% of this total in every scenario comes from dummy producer activation rather than real system cost. This seems large, but it reflects the high penalty price of the dummy producers, not a large amount of energy: across all scenarios the dummies supply only about 0.2% of total demand. Linepacking slightly raises the dummy cost even though it lowers total dummy energy, because the mix of affected nodes shifts between scenarios. The high cost share is therefore an artefact of the dummy penalty price and is set aside in the scenario comparison. Where and why this unmet demand occurs is examined in Section 5.5. The preparatory step is a separate optimisation, so its network costs are not part of the objective reported here. The fixed onshore network and the non-investable generation and storage fleet are identical across all four scenarios by construction, so they cancel in any scenario comparison. This analysis therefore focuses on the components that differ between scenarios: investment in electrolyzers, conversion assets, and offshore network connections, and the operational cost of electricity dispatch.

Table 5.2: Total objective cost per scenario and the dummy producer component. The dummy cost is a penalty artefact and is not part of the component comparison. The remaining objective consists of investment, dispatch, and fixed fleet and network costs. Investment and dispatch costs are analysed in the following sections, while the fixed costs are identical across scenarios and are not compared.

Metric	S1	S2	S3	S4
Total objective (bn EUR)	502.7	523.5	500.6	521.4
Dummy producer cost (bn EUR)	53.5	59.9	57.1	60.6
Dummy cost share	10.6%	11.4%	11.4%	11.6%

5.3.1. Investment cost

The investment costs reported here (Equation 3.20) cover only the assets and connections that are investable in the scenario runs: electrolyzers, hydrogen-to-power conversion, offshore electricity cables, and offshore hydrogen pipelines. OWFs, onshore network reinforcement and other expanding assets are fixed inputs determined before the scenario runs and are identical across all four scenarios, so they are excluded from the results. They remain substantial real-world costs, but because they do not vary between scenarios they do not affect the relative comparison that is the focus here.

Fixed operating costs are excluded, as defined in Section 3.4. They scale electrolyser figures by a near-constant factor and do not change the relative comparison.

Table 5.3 shows investment cost by category and scenario, summed across both milestone years. Total investment cost ranges from 135.2 billion EUR in S3 to 170.7 billion EUR in S4. The offshore electricity network is the largest single category in every scenario, ranging from 82 to 90 billion EUR, which is larger than all electrolyser and other conversion investment combined. Yet the other categories also have significant influences on the differences between scenarios.

Table 5.3: Investment cost by category and scenario, summed over both milestone years. Only investable components are shown. The offshore HVDC cable is the largest category in every scenario; DC-OPF (S2, S4) roughly doubles offshore electrolyser cost and adds hydrogen-to-power conversion that is absent under the transport model.

Category (bn EUR)	S1	S2	S3	S4
HVDC cable (offshore)	82.5	89.6	83.1	89.4
Electrolyser onshore	42.5	46.7	41.8	45.1
Electrolyser offshore	9.8	15.7	8.5	17.1
Hydrogen-to-power conversion	0.0	13.8	0.0	14.2
Hydrogen pipeline (offshore)	2.0	4.9	1.8	5.0
Total	136.8	170.5	135.2	170.7

DC-OPF raises investment cost in three ways relative to the transport model. Offshore electricity cable investment increases by around 7 billion EUR (S1 to S2, from 82.5 to 89.6 billion). Offshore electrolyser investment roughly doubles, from 9.8 billion in S1 to 15.7 billion in S2, and from 8.5 billion in S3 to

17.1 billion in S4, while onshore electrolyser investment rises modestly (around 10%). DC-OPF also triggers around 14 billion of hydrogen-to-power conversion investment that is absent entirely in the transport model scenarios. These assets are sited at the highest-price interior nodes, for the reason that is explained in Section 5.4. These three effects together raise total investment by roughly 25% under DC-OPF. Notably, the extra offshore electrolyser investment does not reduce the offshore cable investment; both rise under DC-OPF. In this model congestion calls for more conversion and more transmission at the same time, rather than conversion substituting for cable investment as in studies where offshore hydrogen avoids electrical infrastructure.

The shift in offshore electrolyser investment is notable given its cost. Offshore electrolyzers are substantially more expensive per MW than onshore, around 58% more in 2030 and 78% more in 2040. The model nonetheless places more capacity offshore under DC-OPF, which means the electricity-side benefit of converting wind to hydrogen near the offshore hubs must outweigh this high investment cost level. This quantifies the trade-off behind the location shift seen in Section 5.2: under DC-OPF, delivering offshore wind to onshore demand becomes costly enough that the more expensive offshore conversion locations become cost-optimal.

Linepacking has little effect on investment cost. Total investment in S3 is about 1.5% lower than S1, and S4 also around 1.5% lower than S2, with the individual categories nearly unchanged in both comparisons. This is consistent with its limited influence on investment location in Section 5.2.

5.3.2. Operational dispatch cost

Figure 5.6 shows annual electricity dispatch cost (Equation (3.19)) by scenario and milestone year. DC-OPF raises dispatch cost relative to its matching transport model scenario, and the increase grows over time. S2 sees an 8% increase compared to S1 in 2030, rising to 14% in 2040. S4 increases by 8% in 2030 and 14% in 2040 compared to S3. In linepacking scenarios dispatch costs are lower compared to scenarios without linepacking. In S3 dispatch costs decrease by 0.7% in 2030 and 1.9% in 2040, and for S4 compared to S2 they decrease by 0.4% and 2.0%. The two effects are close to independent. DC-OPF raises dispatch cost by the same amount whether or not linepacking is active, 8% in 2030 and 14% in 2040. Linepacking also lowers it by a similar amount under both electricity representations.

Dispatch cost is dominated by generator fuel and carbon costs. Storage and hydrogen-to-power conversion costs have a negligible share. Electrolyser operating costs are also small (around 0.4 billion EUR per year by 2040) and nearly constant across scenarios, so it does not affect the comparison. The full generation mix is shown in Appendix E.1, so the dispatched energy can be read alongside the corresponding dispatch cost in Figure 5.6. Dummy producer flows are excluded from the dispatch cost, so the differences reported here are between real generation costs only. The dummy cost differs between scenarios and is reported separately in Table 5.2.

Renewable capacity and availability profiles are identical across all four scenarios, since none are investable, so any difference in their dispatched generation reflects how much of that generation the network can deliver. Under DC-OPF, delivered renewable generation falls by about 33 TWh in 2030 and 38 TWh in 2040 relative to S1, mostly solar and offshore wind. Nuclear generation rises by roughly the same order, around 42 and 45 TWh, and is the main substitute. The nuclear increase exceeds the renewable shortfall because the DC-OPF scenarios also build more electrolyzers, so total electricity consumption is higher. Hydrogen-to-power conversion returns part of this energy to the electricity system later. Fossil generation stays under 1% of supply in every scenario and does not account for the cost increase on its own.

Nuclear is the main substitute because it is the cheapest producer after renewables and hydro, despite its geographic concentration and ramping constraints. In energy terms it provides most of the substitution, but in cost terms the more expensive gas steam and biomass generation contribute a comparable share, which is why dispatch cost rises more than the energy substitution alone would suggest. Hydrogen-to-power conversion also contributes under DC-OPF. Its operational cost is low, and the hydrogen it burns can be produced with cheap electricity and stored, so at some hours it competes with the remaining producers. Under linepacking the same delivered renewable generation changes by less than 0.5 TWh between S1 and S3, against the 33 to 38 TWh shift under DC-OPF, so linepacking is a secondary effect on renewable delivery.

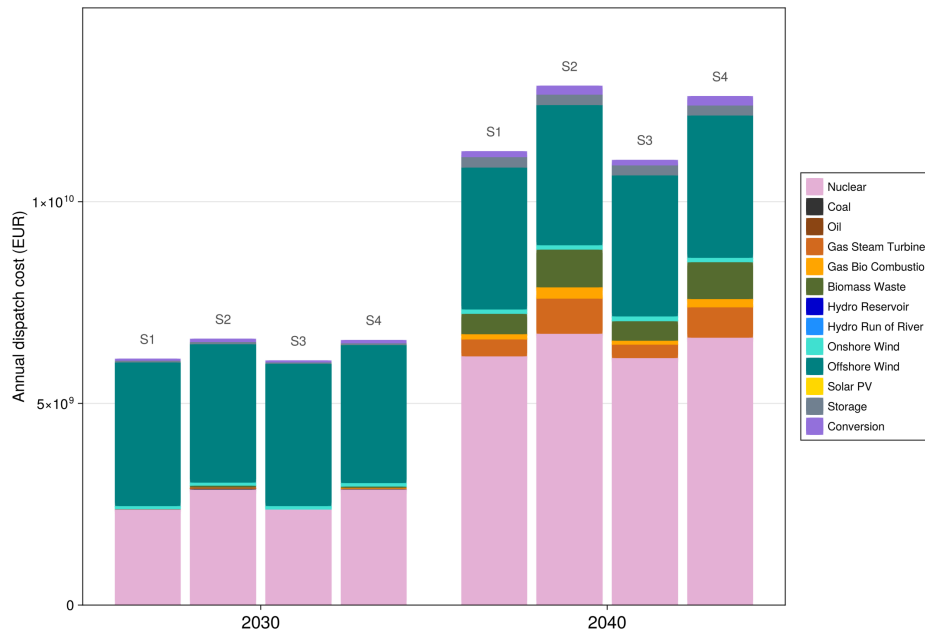


Figure 5.6: Annual dispatch cost by scenario and milestone year. DC-OPF (S2, S4) raises dispatch cost relative to the matching transport scenario (S1, S3), and the gap grows from 2030 to 2040. Linepacking (S3, S4) lowers it slightly. The increase under DC-OPF is the cost of substituting nuclear for wind and solar the network cannot deliver.

Whether this reduced delivery of renewable energy connects to binding corridors and the higher off-shore electrolyser share under DC-OPF is examined in Section 5.5.

Synthesis

Cost confirms and quantifies the findings from Section 5.2. DC-OPF raises both investment and operational cost. On the operational side, dispatch costs increase with 8% in 2030 and 14% in 2040, traceable to a specific mechanism: wind and solar generation that the fixed network cannot deliver is substituted by more expensive generators. On the investment side, DC-OPF roughly doubles offshore electrolyser investment and adds around 14 billion EUR of hydrogen-to-power conversion that is absent in the transport model scenarios. This raises total investment costs by around 25%. Together these point to the same mechanism: under DC-OPF, delivering offshore wind to onshore demand becomes expensive. The model responds by building hydrogen production closer to the offshore hubs despite the higher cost of offshore electrolysers. Whether this is driven by congestion on specific corridors is examined in Section 5.5. Linepacking has a much smaller effect on both cost types. It lowers dispatch cost by around 1 to 2%, growing toward 2040, and changes total investment cost by about 1%.

5.4. Locational energy costs

5.4.1. Nodal prices

Nodal prices are the corrected duals of the consumer balance constraint, averaged over the year as in Equations (3.16) and (3.17). This average summarises the locational cost of electricity at each node. Timesteps in which dummy producers were active are excluded, because the duals in those hours reflect scarcity rather than normal operation. These duals would include artificially high prices which distorts the results of the model the rest of the year. These excluded hours are the system's scarcity hours. Because they are excluded from the average, any effect they have on siting is not captured here, which the next section examines.

Prices are reported in EUR/MWh, and can be compared across nodes, scenarios and milestone years. The coefficient of variation is also reported. It is a unitless measure of how spread out the prices are within a year, which makes it a direct indicator of how evenly the network represents price across locations.

The 2040 nodal prices fall into two clear groups by electricity representation. The transport scenarios (S1, S3) and the DC-OPF scenarios (S2, S4) form two groups, which confirms that the electricity network representation, not linepacking, drives the locational price pattern. In S1 and S3 prices are nearly the same at every node: the coefficient of variation is below 10% and the gap between the 10th and 90th percentile of nodal prices within a scenario is under 7 EUR/MWh. Power moves freely under the transport formulation, so the marginal cost of electricity is almost equal everywhere. In S2 and S4 the spread is much larger, with a coefficient of variation of 40% to 49%. DC-OPF splits the network into separate price areas, because power can no longer route freely around busy lines. Certain nodes show the contrast directly: a mainland node in England (UK15) has a price of 33 EUR/MWh under the transport model but 138 EUR/MWh under DC-OPF, and Luxembourg rises from 30 to 50 EUR/MWh. The same two-group split appears in 2030, at lower and more compressed prices. The transport scenarios have a coefficient of variation of 15% to 16% and the DC-OPF scenarios about 36%, so DC-OPF separates the network in both years. The four-scenario comparison in Appendix E.2 shows this, with S1 and S3 close to each other and S2 and S4 close to each other.

Figure 5.7 shows the 2040 nodal prices under DC-OPF. It makes the price split visible directly. The offshore hubs, Scotland, Denmark, and Norway always have the lowest prices and never appear among the high-price nodes, because they have direct access to high amounts of cheap offshore wind and hydropower. The hub prices stay low and stable across all scenarios, between 20 and 30 EUR/MWh in 2040 and 5 to 10 EUR/MWh in 2030. They barely change between the transport and DC-OPF formulations, because the hubs sit at the source of generation and do not have a native energy demand. The high-price areas are interior, demand-heavy regions that are weakly connected to this cheap generation. In 2030, when prices are lower everywhere, these are southern and eastern Germany, Luxembourg, and an eastern Dutch node. In 2040 the highest prices are in London, Wales, and southern England, with a smaller high-price area in southeastern Germany. These are the places where network constraints stop cheap wind from reaching demand, which raises the local price.

Electrolysers were not investable everywhere. They could be built at 60 candidate nodes: the 13 offshore hubs and 47 onshore hydrogen demand nodes. Many of the high-price areas above, including the English nodes above 70 EUR/MWh in 2040 and most Belgian nodes, were not candidate nodes, so the lack of investment there is a modelling-setup result, not a cost decision. The same applies to some of the largest offshore landings: NL11, which takes the 56.8 GW landing from H5, is not a candidate node either. Capacity near a large landing therefore appears at nearest candidate nodes rather than at the landing itself. Elsewhere, the candidate nodes that receive investment are the cheap ones, which are not necessarily near a landing at all. The meaningful comparison is therefore within the candidate nodes only.

Among candidate nodes, the nodal price is clearly linked to where electrolysers are built. Almost every candidate node with a price above roughly 30 EUR/MWh in 2040 and above roughly 12 EUR/MWh in 2030 receives no electrolyser capacity. For example, nodes where DC-OPF pushes the prices above 35 EUR/MWh such as the English, Welsh and south-east German nodes, receive no capacity. The large investments are at the cheaper candidate nodes, between 20 to 29 EUR/MWh in 2040 and between 5 and 12 EUR/MWh in 2030: the offshore hubs, Denmark, northern Germany, and several French nodes. So a high local nodal electricity price effectively rules a candidate node out. The interior German candidates show this directly. DE2 and DEE0 receive electrolysers under the transport model but nothing under DC-OPF. DE2 holds 1.6 GW in S1 and 2.8 GW in S3 by 2040, and DEE0 holds 3.8 GW in S1 and 1.9 GW in S3, while both receive nothing in S2 and S4. These are interior nodes that stay cheap under the transport formulation but become expensive under DC-OPF, when the network can no longer bring cheap northern power to them. Because the offshore hubs and the northern onshore nodes stay cheap under DC-OPF while interior candidates become more expensive, DC-OPF strengthens the existing northern and offshore siting. The dominant nodes behave in the opposite way. DE94, DK03, and DEF0 stay among the cheap candidates under both representations, so neither representation rules them out, and they hold large capacity in all four scenarios. Which of the cheap candidates receives the most capacity is not settled by the average price, as discussed in the paragraphs below.

Hydrogen-to-power conversion follows the opposite pattern, and only under DC-OPF. The model builds these assets at the highest-price nodes, the interior demand regions the constrained grid cannot reach with cheap power. Because hydrogen moves freely on the backbone, converting it back to electricity at

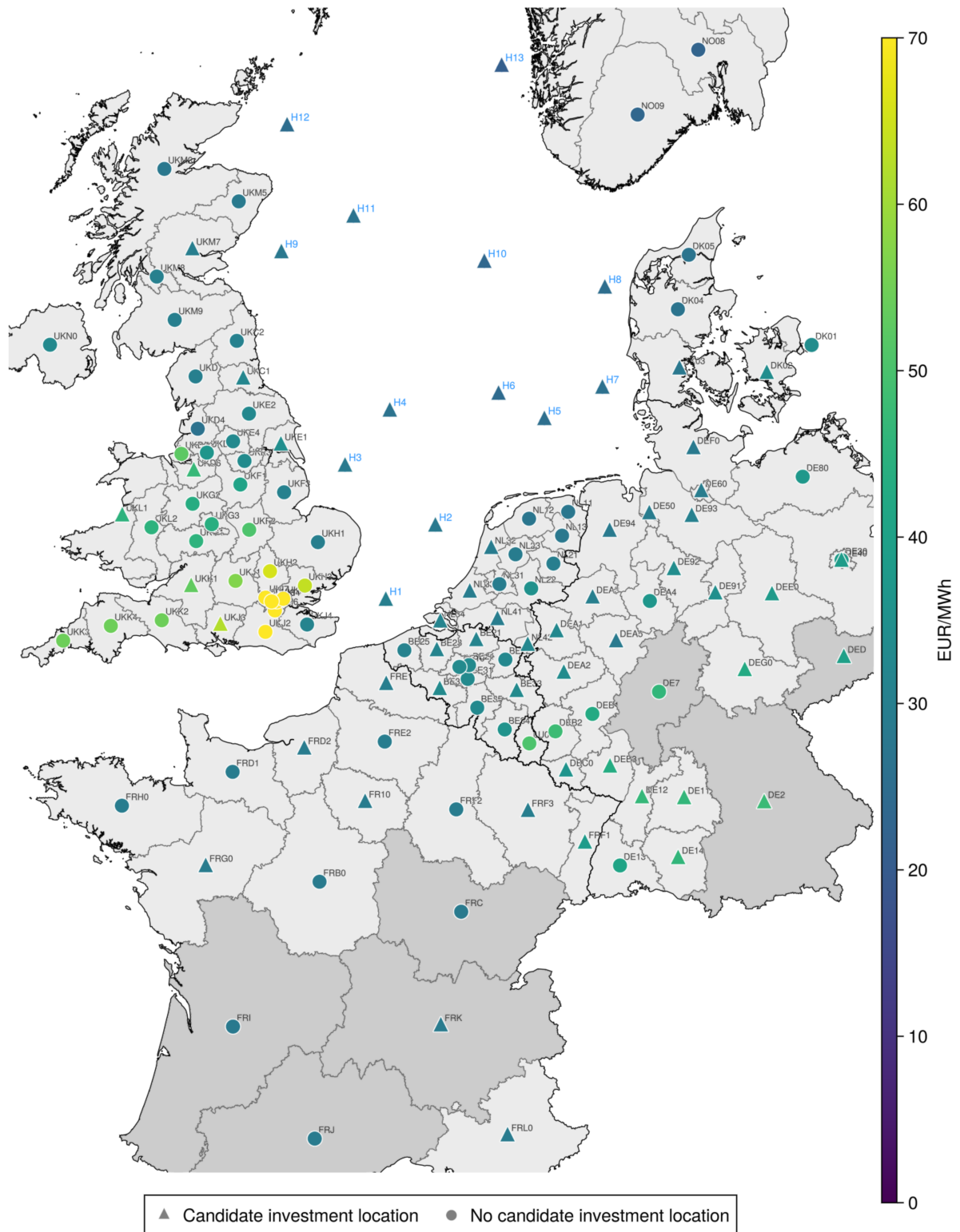


Figure 5.7: Average nodal electricity prices in 2040 under DC-OPF (S2). Colour shows the price at each node. Triangle nodes are electrolyser candidates. DC-OPF splits the network into distinct price areas: the offshore hubs, Scotland, Denmark, and Norway stay cheap, while interior demand regions weakly connected to that cheap generation, notably southern Germany and the London and Wales area, reach much higher prices. Candidate nodes in these high-price areas receive no electrolyser investment (Section 5.2).

such a node is a way to serve demand that the electricity network cannot deliver to directly. The same price landscape that pushes electrolyser toward the cheap northern and offshore nodes therefore pulls conversion toward the expensive interior ones. Conversion capacity is excluded from the electrolyser onshore-offshore share reported here and is a DC-OPF-only feature. Its cost is reported in Section 5.3. These assets do not eliminate the unmet demand. Building enough conversion capacity to cover the scarcity hours would cost more in capital investments than the dummy energy operational costs in total, because the shortfall occurs in a small number of hours per year. Covering every peak is therefore not attractive, even though the conversion capacity that is built does serve some of that demand.

Within the group of cheap candidate nodes, the electricity price alone does not decide the outcome. These nodes differ by a few EUR/MWh among the onshore candidates, and the order of investment does not follow the order of price. Some cheap hubs or onshore nodes with the lowest average prices sometimes receive no electrolyser investments. Electricity and hydrogen transport carry zero operational cost, so moving power or hydrogen between nodes is free and does not influence it. Investment cost per MW is equal across onshore candidates. Local hydrogen demand does not decide it either: the correlation between a node's hydrogen demand and its electrolyser investment is near zero, because the uncongested backbone lets hydrogen be produced anywhere and delivered cheaply. BE21 has the second-highest hydrogen demand but receives no electrolyser, while DK03 has low local demand but a large one.

What the reported averages cannot resolve is the hourly price dynamics. The electrolyser responds to the hourly price, not the annual average, and two nodes with the same average price can have different hourly price shapes. A flexible electrolyser would plausibly prefer a node with a few very cheap hours, since it does not have to follow local hydrogen demand hour by hour: the backbone and hydrogen storage let production and consumption be separated in both place and time. The placement among the cheap candidates is therefore plausibly decided by this hourly interplay of price and demand, which sits below the resolution of the average-based prices reported here. The average price rules an expensive node out, but the ranking among the cheap ones would depend on hourly behaviour that these averages do not capture.

The hydrogen nodal prices behave differently from electricity. In every scenario the hydrogen price is almost the same at every node, with a coefficient of variation around 1%. The hydrogen backbone is not influenced heavily by DC-OPF constraints, and hydrogen carries almost no locational price signal. The locational price effect of network representation is therefore an electricity effect, not a hydrogen one.

5.4.2. Dummy producer activation

Dummy producers supply demand that the system cannot otherwise meet, at a high penalty cost of 999 EUR/MWh at nodes which are connected to other countries in real life, representing import, and 9999 EUR/MWh at internal nodes. Their activation shows where and when demand cannot be met. It is a necessary addition to keep the model feasible, and it is reported here as a metric to show system stress. Across all four scenarios the dummies supply only about 0.2% of total energy.

No dummy activation occurs in 2030 in any scenario. All activation is in 2040. In 2030 the system meets demand at every node without any dummy penalty, while in 2040 higher demand pushes the system into scarcity in the strictest representative period. The activation is therefore a 2040 phenomenon throughout.

The amount and timing of activation differs between the transport and DC-OPF scenarios (Table 5.4). The transport scenarios fail in only 9 timesteps (S1) and 8 timesteps (S3), all within a single representative period. The DC-OPF scenarios fail in 29 timesteps (S2) and 28 timesteps (S4), spread across two representative periods. DC-OPF therefore roughly triples the number of scarcity hours. Total dummy energy need rises from 6.59 TWh in S1 to 6.95 TWh in S2, and from 6.46 TWh in S3 to 6.81 TWh in S4. In every scenario, unmet demand at internal nodes make up about 79% of the dummy energy, with the rest at import nodes.

The activation has two distinct causes, and the scenarios separate them. In the transport scenarios, every generator that still exists in 2040 is at its maximum available output during the scarcity hours. Coal and oil plants, which exist in 2030, are fully phased out by 2040 and cannot contribute. The

Table 5.4: Dummy producer activation in 2040 by scenario. No activation occurs in 2030 in any scenario. Scarcity timesteps are the number of representative-period timesteps in which at least one dummy producer is active. Dummy energy is the total annual unmet demand supplied by dummy producers.

Scenario	Scarcity timesteps	Nodes affected	Dummy energy (TWh)
S1	9	59	6.59
S2	29	84	6.95
S3	8	46	6.46
S4	28	78	6.81

shortfall is therefore a genuine generation shortage in the strictest representative week, not a network limitation. This is confirmed by the preparatory optimisation: when the full network was investable, it needed exactly the same dummy activation as the base case, showing that the model could not resolve the problem by expanding network capacities. In the DC-OPF scenarios, by contrast, several generators are below their maximum output during the scarcity hours while the dummy still activates. Here the producer energy is available but cannot be transported to demand nodes because of the network physics constraints. The additional DC-OPF activation is therefore a delivery failure, on top of the underlying generation shortage.

The spatial pattern matches this (Figure 5.8). The transport scenarios fail at 59 (S1) and 46 (S3) nodes. The DC-OPF scenarios fail at 84 (S2) and 78 (S4) nodes. Under DC-OPF, 38 nodes fail that do not fail in the base case, spread across Belgium, France, Luxembourg, and Dutch nodes. These are interior, demand-heavy regions that are weakly connected to cheap generation. The regions with the highest dummy activation are the same as those with the highest nodal prices, though activation appears more widely at a lower level. The dummy activation and the price dispersion are therefore two views of the same effect: DC-OPF prevents cheap power from reaching these regions, which raises their price in normal hours and leaves their demand unmet in the strictest hours.

5.5. Network congestion and electricity flows

This section examines how heavily the network is used and where it constrains the system, through line utilisation (Equation (3.21)), and the marginal value of line capacity, which is the corrected transport flow limit dual (Equation (3.18)). Unlike the nodal price analysis in Section 5.4, where dummy-active hours were excluded, all hours are included in the utilisation figures. Utilisation is bounded at 100% regardless of cause, so scarcity hours cannot inflate it the way they inflate the nodal price dual. Including these hours is therefore safe, and they are informative, since they show the network at its most heavily loaded. The line duals are treated as the nodal prices were, with dummy-active hours excluded, since they are subject to the same distortion.

5.5.1. Onshore electricity network

The transport model and DC-OPF produce opposite utilisation patterns. In the transport scenarios (S1, S3) the onshore lines are used heavily: average utilisation across all lines is about 75% in 2040, and most lines reach full capacity at some point in the year. In the DC-OPF scenarios (S2, S4) average utilisation is much lower, around 40%, and far fewer lines ever reach capacity.

A line loaded at its maximum capacity is not necessarily a problem. The network was sized in the preparatory optimisation to be used cost-optimally under the transport model, so lines reaching capacity reflect efficient use of transport rather than a shortfall. What matters is whether that limit forces the system into a more expensive dispatch, which is what the transport flow limit dual measures. A small dual means the limit binds but relieving it would lower system cost only slightly. A large dual means the limit traps cheap generation and forces more expensive supply elsewhere, so relaxing it would save more. Utilisation shows whether a line is loaded to capacity, the dual shows whether that is a problem. So although DC-OPF shows lower utilisation, it is the more congested formulation, because its binding lines carry far higher duals.

This congestion rises from 2030 to 2040. As demand grows, the binding duals rise. On the most constraining corridor, UKI5 to UKJ4, the average dual rises from about 8 EUR/MWh in 2030 to about

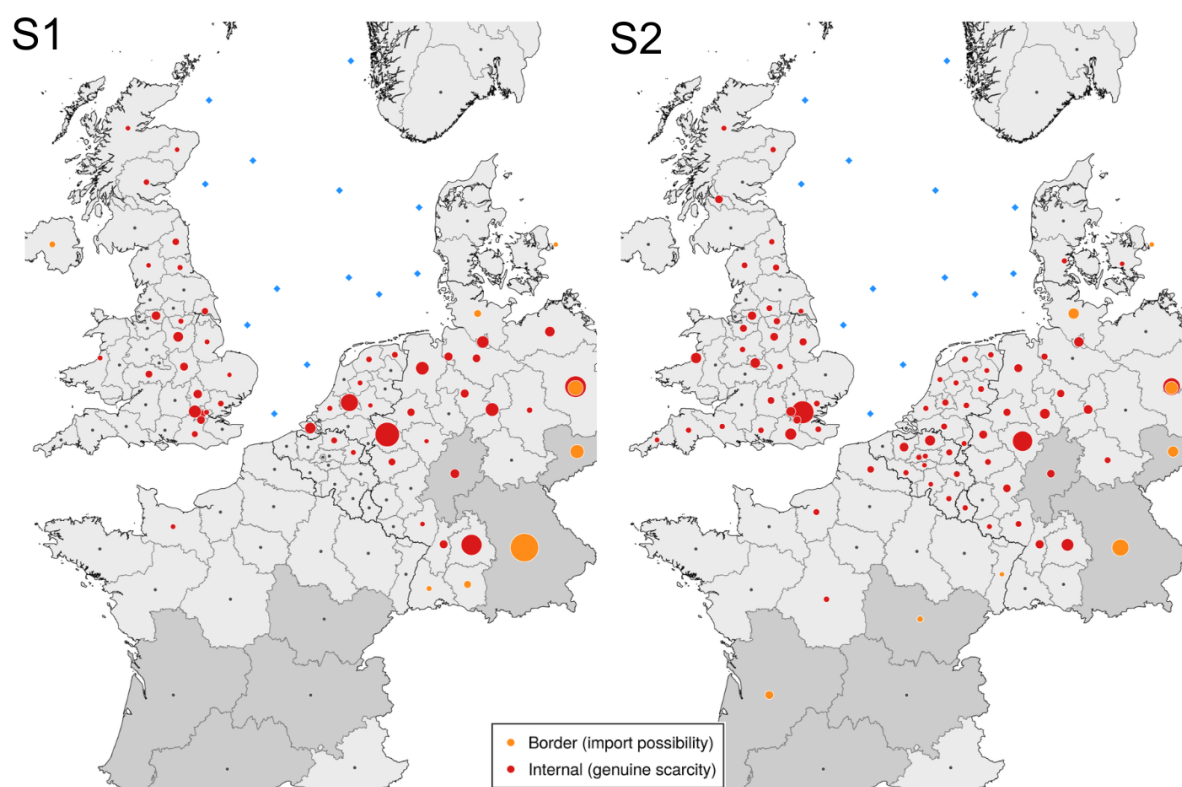


Figure 5.8: Dummy producer activation in 2040 by node and scenario. Circle size is the annual unmet demand at each node in TWh. Red circles are internal nodes (9999 EUR/MWh penalty), orange are import nodes (999 EUR/MWh). The transport scenarios (S1, S3) fail at fewer. the DC-OPF scenarios (S2, S4) fail at more interior nodes across Belgium, France, Luxembourg, and the Netherlands. No activation occurs in 2030 in any scenario.

200 EUR/MWh in 2040, and several other England and Germany corridors intensify in the same way.

Figure 5.9 shows the most constraining onshore lines under DC-OPF in 2040. These corridors match the high-price and unmet-demand regions found earlier. The most strongly binding lines are in England, the corridor from UKI5 toward UKJ4 and the UKH1 to UKH3 link, the France to Luxembourg connection (FRF3 to LU00), and several lines in interior Germany (around DE7 to DEA5 and DEB1 to DEB2). The lines with the highest dual values are listed in Table 5.5. These are exactly the regions that showed the highest nodal prices and the most dummy activation. The line constraints therefore explain the locational price differences and the unmet demand: cheap northern wind cannot physically reach these interior regions easily, which raises their price in normal hours and leaves their demand unmet in the strictest hours.

Table 5.5: Most constraining onshore electricity lines under DC-OPF (S2) for 2030 and 2040. Average dual value is the corrected dual of the transport flow limit in EUR/MWh, averaged over hours without dummy activation. Percent binding is the share of all hours, including dummy-active hours, in which the line is at its limit. Lines are ordered by their 2040 dual.

From	To	2030		2040	
		Avg. dual val.	Pct. binding (%)	Avg. dual val.	Pct. binding (%)
UKI5	UKJ4	7.9	16	200.8	50
UKH1	UKH3	0.9	18	81.3	63
FRF3	LU00	36.9	50	76.0	64
UKI7	UKJ1	0.0	0	63.6	1
DE7	DEA5	11.5	20	51.0	29
DEB1	DEB2	34.5	62	44.5	52
UKD4	UKD7	4.0	27	37.6	67
UKJ3	FRD1	3.6	96	33.9	84
BE32	FRF2	2.0	30	20.3	22
NL22	NL41	18.3	26	16.0	44
FRC	FRF1	10.1	29	12.1	42
BE34	LU00	5.8	26	9.1	27
DE2	DE7	9.5	49	7.0	58
DK03	DK02	5.4	43	6.5	40
DE12	DEB3	23.8	68	4.2	21

In S1, the most constraining lines are mostly interconnectors, including the Norway to UK link and the Norway to Denmark and Netherlands links. Under DC-OPF these interconnectors are still constrained, in some cases more than before, but several interior lines now rank among the most constraining too, often higher than the interconnectors.

5.5.2. Hydrogen backbone

The hydrogen pipelines are used heavily in every scenario. Average pipeline utilisation is around 60% in 2040 and pipelines are at capacity in 35% to 41% of hours. Despite this, hydrogen prices are almost uniform across the network, as found in Section 5.4. This is the same pattern as the onshore electricity network under the transport model: hydrogen always uses the transport formulation, with no physical flow constraints, so the model can route hydrogen around any single full pipeline. Heavy use therefore does not directly create large price differences. Linepacking does not change this pattern. Hydrogen prices stay close to uniform with or without it.

5.5.3. Offshore network and wind curtailment

The offshore cables are used heavily in all scenarios, with average utilisation around 83%. This has two reasons. Their capacities are an investment decision in each scenario, so the model sizes them to be well used. Additionally they are point-to-point HVDC links not subject to the DC-OPF flow constraints, so power is not rerouted away from them as on the constrained AC network. The more informative result is offshore wind curtailment (Equation (3.22)). Table 5.6 shows it for all scenarios and years.

This curtailment is the generation-side counterpart of the binding corridors above. The wind is stranded because the same constrained lines that carry the highest duals cannot move it from the northern coast to interior demand. DC-OPF raises curtailment clearly in 2030, from 21.0% to 24.1% comparing S2

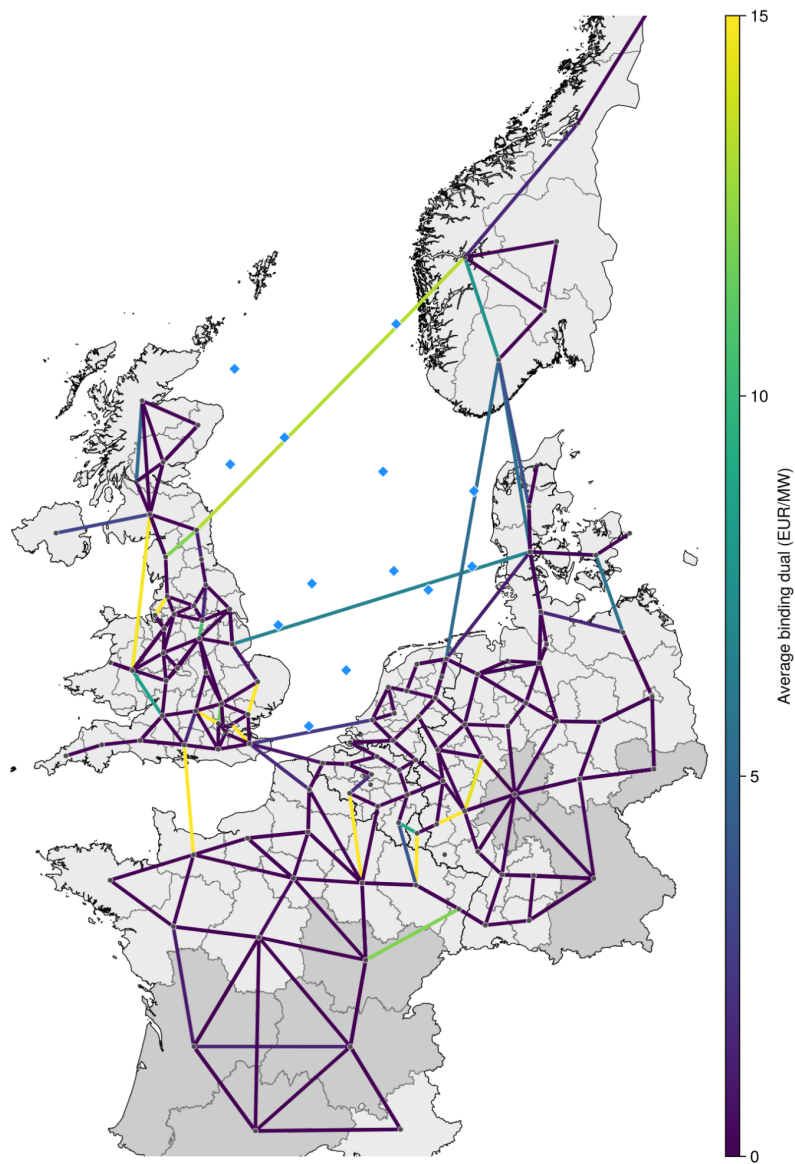


Figure 5.9: Most constraining onshore lines under DC-OPF (S2) in 2040. Line colour shows the average transport flow limit dual in EUR/MWh. Lighter means a higher dual, so relieving that line would reduce system cost more. The strongest constraints are in England (UKI5 to UKJ4, UKH1 to UKH3), the France to Luxembourg link, and interior Germany. These are the corridors that separate cheap northern generation from interior demand, and they match the high-price and unmet-demand regions in Sections 5.4 and the dummy activation results.

Table 5.6: Offshore wind curtailment by scenario and milestone year, as a share of available generation. DC-OPF (S2, S4) raises curtailment in 2030 and has a smaller effect in 2040. Linepacking lowers curtailment only in 2040 and only when DC-OPF is active.

Scenario	2030 curtailment (%)	2040 curtailment (%)
S1	21.0	19.4
S2	24.1	20.4
S3	21.6	19.9
S4	24.2	19.2

to S1, while in 2040 the difference is much smaller, from 19.4% to 20.4%. Offshore electrolysis is one candidate explanation, since offshore capacity grows from 4.0 GW in 2030 to 12.4 GW in 2040 in S2 (while less in S1), and conversion at the hubs absorbs wind the constrained network cannot carry inland. Whether this accounts for the weaker 2040 effect is not tested here, and other factors change between the two years as well.

Linepacking scenarios have less curtailment, but only when DC-OPF is active. In 2040 curtailment falls from 20.4% in S2 to 19.2% in S4, while there is no such reduction between S1 and S3, and in 2030 linepacking slightly raises it in both pairs. The flexibility from linepacking might help to absorb stranded wind when the network is physically constrained. Curtailment is present under the transport model as well, but linepacking does not reduce it there. The flexibility only lowers curtailment on top of the additional stranding that DC-OPF causes. A possible mechanism is the within-block shifting that linepacking enables. An electrolyser can move its consumption into the cheapest hour of a block, and under DC-OPF those cheap hours are more frequent (Section 5.6). Where a cheap hour coincides with stranded wind, that shifting converts electricity that would otherwise be curtailed. This is consistent with linepacking reducing curtailment only when DC-OPF is active, although the link is not measured directly.

5.6. Electrolyser operation patterns

This section examines how electrolysers operate hour to hour, and whether the linepacking flexibility is actually used. Linepacking changed the investment results only slightly (Section 5.2) and provided a small cost saving that grew toward 2040 (Section 5.3). The question here is whether electrolysers use the extra flexibility, and how.

All metrics below use the corrected nodal prices defined in Equation (3.16), and compare prices only within a single scenario and year. Only nodes and years where an electrolyser is actually built are included, since a node without an electrolyser cannot respond to prices.

5.6.1. Flexible operation in cheap hours

In every scenario, electrolysers run mostly when electricity is cheap. The flexible operation ratio (Section 3.4) captures this: a ratio below one means the electrolyser buys more in cheap hours.

In 2040 the electrolysers pay about half of the time-average price in all four scenarios: the hourly price ratio is 0.50 in S1, 0.49 in S2, 0.49 in S3, and 0.48 in S4 (Table 5.7). So electrolysers behave as flexible load in every scenario, running when power is cheap and idling when it is expensive. This behaviour does not depend on linepacking.

Cheap-hour operation happens at two time scales, and only one of them is the linepacking effect. The coarse scale is choosing which four-hour blocks to run in, the fine scale is choosing which hour within a block. Any flexible electrolyser can pick cheap blocks, with or without linepacking. What linepacking adds is only the freedom to move consumption within a block, since it replaces the hourly hydrogen balance with a block-level one.

The block price ratio isolates the coarse scale. For this ratio each block is treated as a single step: one average price and the total electricity used across its four hours. Because it works on whole blocks, it cannot see how consumption is arranged inside a block, only which blocks the electrolyser favours (Section 3.4). It is about 0.49 to 0.52 in every scenario. The scenarios without linepacking have no four-hour hydrogen blocks, so their output is grouped into the same four-hour windows to make the comparison. That the ratio is similar across all four scenarios is the point: block selection is present with and without linepacking, so it is not the linepacking effect. Hydrogen storage, present in every scenario, already lets production shift in time, so this shared block-level cheap-buying does not require linepacking. The only scale left for linepacking to act on is within the block, which the next section examines.

5.6.2. The effect of linepacking

Linepacking lets an electrolyser vary its electricity use hour by hour within a four-hour block, as long as the total hydrogen output over the block is met. Without linepacking the hydrogen balance is enforced every hour, so this within-block shifting is not possible.

Table 5.7: Hourly price ratio is the average nodal price the electrolyser actually operates at (energy-weighted by its hourly consumption) divided by the hourly-average nodal price at that node over the year. Below 1 means it concentrates consumption in cheaper hours. Block price ratio is the flexible operation ratio computed over four-hour blocks (Section 3.4). It is also near 0.5 in every scenario, so block-level selection does not depend on linepacking. Variable blocks is the share of active blocks in which the price differs across the four hours in representative periods. It applies only to the linepacking scenarios (S3, S4). Cheapest-hour share is the average share of a variable block's electricity used in its single cheapest hour (against 25% under an even split over all hours). All four scenarios buy at about half the average price (ratio near 0.5). The last two columns isolate the within-block effect that only linepacking enables.

	Hourly price ratio	Block price ratio	Variable blocks (%)	Cheapest-hour share (%)
S1	0.50	0.52	n/a	n/a
S2	0.49	0.50	n/a	n/a
S3	0.49	0.50	12	50
S4	0.48	0.49	31	57

The effect is the most clear in blocks where the electricity price changes within the block. This happens in about 12% of the active blocks in S3 and 31% in S4. The higher share in S4 is because DC-OPF creates more price variation in time and place, which gives linepacking more to exploit.

In these fluctuating price blocks, the electrolyser puts almost all of its electricity into the cheapest hour. On average the cheapest hour of the block takes 50% of the block's electricity in S3 and 57% in S4, against 25% if the input were spread evenly. The most expensive hour of the block takes almost zero. The cheap-hour share is limited by the electrolyser capacity, which defines how much can be drawn in a single hour. Figure 5.10 shows a few example blocks for an electrolyser at location DEB3. Electricity is only used as input in the timestep with the lowest price within the four-hour blocks. If there are multiple timesteps with the lowest price, the electricity input can be in multiple (Block 5 and Block 9). In blocks where the nodal prices are the lowest, the electrolyser increases its production significantly.

This is the only mechanism linepacking adds, and it comes from the electrolyser and other conversion assets sitting between two systems with different temporal resolutions. On the electricity side it faces an hourly price, on the hydrogen side it has to deliver a fixed total over each four-hour block rather than a fixed amount every hour. It can therefore move its electricity draw to the cheapest hour of a block, but only in the blocks where the price varies, which is a minority in S3 and a larger share in S4. The electrolyser's own operational cost is a fixed rate per unit of hydrogen and does not change when it shifts hours. The saving instead falls on the generation side: by consuming when the nodal price is low, the electrolyser draws on cheaper marginal generation and avoids more expensive dispatch, which lowers total system cost. This saving appears in the dispatch cost of Section 5.3, and it is larger under DC-OPF because within-block price variation is more common there.

Summary

Electrolysers act as flexible load in all scenarios, running in cheap hours and cheap blocks and paying about half the average nodal price. Linepacking adds one extra ability: within a four-hour block, it shifts electricity use to the cheapest hour. This only matters in the blocks that have price variation, which is why its overall effect is small but real, and larger under DC-OPF where price variation is more common. This explains the modest operational cost saving from linepacking found in Section 5.3, and why that saving was larger when DC-OPF was active.

5.7. Sensitivity analysis

The conclusions of this study are based on the cost-optimal distribution of onshore and offshore electrolyser capacity. This section tests whether that distribution is robust to the input parameters and assumptions that are most likely to affect it. The chosen parameters are varied while all other inputs are held at the original values, and the effect on the onshore and offshore invested electrolyser capacity is analysed. The tests are run on the base case (S1) and the DC-OPF case (S2). S1 provides the baseline without congestion and S2 shows the effect when DC-OPF is active. The linepacking scenarios are omitted, because linepacking was shown to have little influence on the investment distribution.

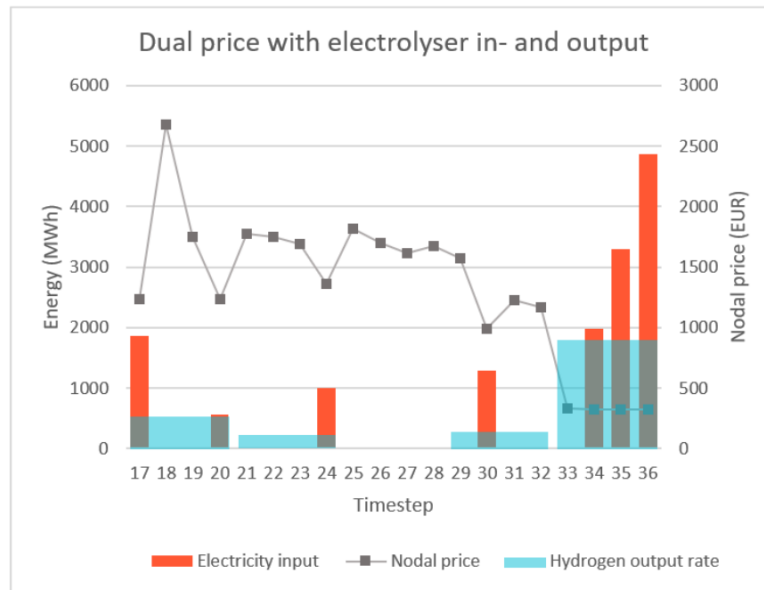


Figure 5.10: Electrolyser electricity use across four-hour blocks at node DEB3 under linepacking, for a set of example blocks. Orange bars show electricity input per hour, the line shows the nodal price, blue bars show electrolyser output rate per four-hour block. The electrolyser concentrates its input in the lowest-price hours of each block and uses none in the higher-price hours. Where multiple hours share the lowest price, input is distributed between them (blocks 5 and 9). This within-block shifting is the flexibility that linepacking adds. Without it the hydrogen balance is enforced every hour and the input cannot move within the block.

The choice of parameters is based on how the siting decision is made. A parameter can change the onshore-offshore distribution if it changes the relative cost of building or supplying an electrolyser at a location, or the network congestion that separates their prices. A parameter that shifts costs or prices uniformly changes the whole system without influencing where electrolysers are cheapest to build. The analysis therefore focuses on the parameters that act on the onshore-offshore trade-off or on the congestion behind it.

The primary parameter is the offshore electrolyser cost premium, the additional capital cost of building an electrolyser at an offshore hub rather than onshore. This premium is the direct economic barrier to the locational advantage of being close to offshore wind, and the finding that electrolysers remain mostly onshore depends on it. A smaller premium makes offshore siting more attractive, and a larger premium suppresses it. It is therefore the parameter that is most likely to overturn the central conclusion. It is varied from a zero premium up to double the base premium, to map the full relationship and find whether and where the conclusion changes. Not all of these values appear in the literature, but the extremes are included to show the full shape of the relationship. The two cost sources that specify offshore electrolyser costs, NSWPH (Hartvig et al., 2025) and TYNDP (ENTSO-E & ENTSOG, 2024), differ mainly in their overall cost level rather than in the premium: the offshore-to-onshore ratio is close to identical in both. A different absolute cost level therefore might change the total capacity built without changing the distribution. The premium, not the level, is the parameter that matters for siting.

Two further tests show influences on congestion in the model. Electricity and hydrogen demand are each varied by 20%, because demand changes how heavily the network is loaded, and therefore the congestion that creates locational price differences. Furthermore, line capacities are scaled upward, to test whether relieving congestion removes the offshore advantage. This also checks how the result depends on the assumed network size, since the fixed capacities are the cost-optimal result of the preparatory run rather than a free choice. The capacity is only increased, not decreased. A lower capacity would push the already constrained 2040 network into more unmet demand, with artificial high nodal prices. The result could be driven by the dummy producers rather than by real siting decisions, so a reduction would not give a meaningful siting signal.

Some parameters with uncertain values are not varied, because they are unlikely to affect the siting distribution. The CO₂ price and fuel costs are not tested because fossil generation is below 1% of

supply in every scenario, so even a large change moves little generation and does not change the marginal technology at most nodes. The discount rate applies the same annualisation to onshore and offshore electrolyzers, which share an economic lifetime, so it does not change their relative capital cost. The offshore HVDC cable cost is not varied separately. It acts on the same trade-off as the offshore electrolyser premium: both raise the cost of siting hydrogen production offshore relative to onshore. Varying the offshore premium therefore already captures this direction of sensitivity, and a separate cable-cost test would move the offshore share the same way.

Table 5.8 reports the offshore share and the total electrolyser capacity for every test, in both scenarios and both years. The original model results are in the top row. The discussion below groups the tests by what they change: the offshore cost premium, the demand level, and the network capacity.

Table 5.8: Offshore share and total electrolyser capacity under each sensitivity test, for the base case (S1) and the DC-OPF case (S2), in 2030 and 2040. Share is offshore capacity divided by total electrolyser capacity. The offshore investment cost premium is about 58% in 2030 and 78% in 2040.

Test	S1 (Base case)				S2 (DC-OPF)			
	2030		2040		2030		2040	
	Share (%)	GW	Share (%)	GW	Share (%)	GW	Share (%)	GW
Original results	0.0	17.3	12.5	65.7	17.7	22.6	16.4	75.6
Zero premium	46.3	16.8	60.8	62.6	47.3	22.0	64.0	78.3
Half premium	13.0	17.2	21.7	64.7	29.9	22.5	35.8	76.4
Double premium	0.0	17.3	2.6	66.3	0.0	22.8	5.1	75.7
Electricity demand +20%	1.8	29.7	11.7	70.2	10.0	30.6	17.8	90.4
Electricity demand -20%	0.0	16.3	7.0	55.9	3.2	17.8	2.9	58.1
Hydrogen demand +20%	0.4	21.0	16.8	78.4	16.8	26.0	21.3	86.5
Hydrogen demand -20%	0.0	13.7	3.9	53.7	12.5	19.3	13.6	66.3
Line capacity +25%	0.0	17.2	10.7	64.7	12.2	18.4	11.0	66.7
Line capacity +50%	0.0	17.0	7.4	64.3	5.7	17.1	4.7	65.1

5.7.1. Offshore cost premium

The premium is the strongest lever on the siting distribution. Lowering it moves capacity offshore, and raising it removes offshore investment almost entirely. At zero premium (where onshore and offshore electrolyzers are equally expensive) the offshore share jumps to about 61% in S1 and 64% in S2 in 2040, so offshore becomes the majority in both scenarios. At half the base premium the offshore share is still a minority, 22% in S1 and 36% in S2. At double the base premium offshore nearly disappears, falling to 3% and 5%. The distribution therefore changes as expected across the tested values, from majority to almost none. The threshold where offshore has the highest share lies below half the base premium, which is within the range used in the literature. Used data sources like NSWPH (Hartvig et al., 2025) and TYNDP (ENTSO-E & ENTSG, 2024) with premiums above 50% are high end of value compared to the analysed literature. Gea-Bermúdez et al. (2023), Glaum et al. (2024), Travaglini et al. (2025) and Löhr et al. (2023) use offshore electrolyser costs which range from almost zero to 56%. At the lower end of that range the model would place a much larger share of electrolyser capacity offshore, and offshore could become the majority. The onshore dominance found here is therefore conditional on a relatively high offshore premium, and is not robust across the full range of published cost assumptions. The total capacity barely changes across these tests, which shows the premium changes where electrolyzers are built, not how many. The DC-OPF effect itself is unchanged by the premium. At every tested premium the DC-OPF case has a higher offshore share than the base case, in both years. The premium sets the level of offshore deployment, while the representation shifts it in the same direction regardless of that level.

5.7.2. Demand

Both electricity and hydrogen demand are varied by 20%. Changing demand mainly changes how much capacity is built, and only moves the distribution through congestion. Raising either demand increases total capacity. The largest change is from higher electricity demand under DC-OPF in 2040, where the

total rises from 76 in the original results to 90 GW. Lower demand reduces total capacity correspondingly. The effect on the offshore share works through congestion. Lower electricity demand shows it most clearly: in 2040 it reduces the S2 offshore share from 16% to 3%, because relieving the network declines locational price differences and removes the offshore advantage. Higher electricity demand has little effect in 2040, raising the S2 share only little, because the network is already congested and the extra demand is met by building more capacity in the existing locations. Hydrogen demand acts in the same direction but more evenly. Higher hydrogen demand raises the offshore share by about 4 to 5 points in 2040 in both scenarios, and lower hydrogen demand reduces it. In every demand case the offshore share stays a minority.

5.7.3. Network capacity

Expanding the network confirms that the offshore share is driven by congestion. Adding line capacity reduces the offshore share under DC-OPF, and the effect grows with higher capacities. In 2040 the S2 offshore share falls from 16% at the base to 11% with 25% more capacity, and to 5% with 50% more. More transmission lets cheap northern power reach the demand that was previously constrained, which removes much of the locational advantage that offshore hubs had. The total capacity is almost unchanged, so this is a pure relocation effect. The result supports the central mechanism of this study: the offshore investment that appears under DC-OPF is a response to network congestion, and relieving that congestion shifts it back onshore.

5.7.4. Summary

The DC-OPF effect is robust across the tests. In every case DC-OPF raises total electrolyser capacity and brings more of it forward into 2030, and in almost every case it raises the offshore share relative to the base case. The two exceptions are 2040 with 20% lower electricity demand and 2040 with 50% more line capacity, which are the tests that relieve congestion most strongly. That the effect disappears precisely where congestion is removed supports rather than weakens the mechanism: the offshore shift under DC-OPF exists because the network binds, so it should vanish when it no longer does.

Regarding the onshore-offshore distribution itself, only the offshore cost premium can overturn the onshore dominance. The premium assumed here is at the high end of the literature, and the lower premiums used by other studies would move a substantial share of electrolysis offshore. Demand and network capacity change the offshore share through congestion, but not enough to make offshore the majority. The total electrolyser capacity responds mainly to demand, while the distribution responds mainly to the premium, and more weakly to congestion. The conclusion that cost-optimal electrolyser investment is predominantly onshore is therefore robust to demand and network assumptions, but conditional on the offshore cost premium, which is the single most influential parameter.

5.8. Conclusion on results

This chapter reported the cost-optimal electrolyser locations under the four scenarios and the mechanism behind it. Electrolyser investment is predominantly onshore in every scenario and both milestone years, above 80% throughout, with offshore capacity appearing only as an addition at a few hubs and reaching at most 18.3%. Moving from the transport formulation to DC-OPF shifts capacity toward the offshore hubs and northern nodes, brings it forward into 2030, and raises the total built by about 15%. Linepacking leaves the long-run siting close to the base case and acts mainly on how electrolysers operate within the day.

The mechanism behind the siting is locational: enforcing DC-OPF separates the network into distinct price areas, because power can no longer route freely around binding lines. The offshore hubs and northern nodes stay cheap while interior demand regions become expensive, and a high average nodal price rules a candidate node out while a low price does not directly determine which cheap nodes are chosen. The binding transport-flow duals on the corridors between cheap generation and interior demand explain both the price separation and the unmet demand at the interior nodes. The sensitivity analysis shows the onshore-dominant result is robust to demand and network capacity but conditional on the offshore cost premium, which is the single most influential parameter.

A second robustness check comes from an exploratory extension to 2050 (Appendix D). Onshore dominance not only holds but strengthens there, with the offshore share falling to 3 to 5%. This is for a

different reason than in 2030 and 2040: almost all renewable generation added toward 2050 is onshore, so the new cheap power is onshore and electrolysis follows it. This appears in the transport scenarios as well as the DC-OPF scenarios, so it is a generation-mix effect rather than a representation effect. The 2050 magnitudes are shaped by an inconsistency in the demand and supply projections and are not directly comparable with the results above, but the direction is clear. The findings of this chapter are interpreted against the literature in the next chapter.

6

Discussion

This chapter interprets the results and links them back to the literature and their limitations. The research question asks how electricity grid and hydrogen network representations influence the cost-optimal location of hydrogen production in the North Sea region. Chapter 5 shows the mechanism behind the results, how the network representations produce the siting, price, and cost patterns. This chapter takes these main findings, and asks what they mean against prior studies and how far it can be trusted.

The two representations act on different decisions. DC-OPF changes the locational cost of electricity, which changes where an electrolyser is cheapest to build. Linepacking adds short-term operational flexibility, which changes how an electrolyser runs within four-hour blocks but not where it is cheapest to build. One acts on the investment decision, the other on operation.

6.1. Implications for the literature

Chapter 2 showed that the literature does not agree on where hydrogen should be produced in the North Sea, and argued that the disagreement is patterned. Studies differ on many things at once: system boundary, cost assumptions and other parameters, spatial resolution, and how they represent the electricity and hydrogen networks. Because these vary together, no existing study can explain what the network representation alone does to the location result. This study isolated it. It held the system boundary, the costs, the resolution, and the data fixed, and varied only the network representation. This choice affects the answer.

The direct comparison is with Cao et al. (2021), the one study that varied the electricity grid representation in a controlled way. They switched between transport, DC optimal power flow, and PTDF in the same model and found almost no difference, with grid investment changing by around 5% and other indicators by under 1%. They attributed this result to their country-level resolution, where one node per country is too coarse for any method to represent internal congestion. At the more detailed resolution in this research the congestion does appear. At NUTS-2 resolution the same switch, from transport to DC-OPF, changes total electrolyser capacity by about 15%, brings offshore investment forward, and raises the offshore share. The representation matters once the resolution is fine enough to represent the congestion caused by the DC-OPF constraints. This does not contradict Cao et al. (2021). It confirms the condition they identified, on a different outcome variable, electrolyser location, which they did not study.

The system-level studies that disagree, Gea-Bermúdez et al. (2023) favouring onshore and Glaum et al. (2024) favouring offshore, differ on several assumptions at once, including HVDC cost, offshore spatial resolution, and how hydrogen demand is treated. This study cannot say which of those assumptions drove their conclusions, because it did not vary them. What it adds is a separate axis they share but did not test: both use a transport-based electricity representation without physical flow constraints. They both note this as a limitation of their own model. This study shows what that shared choice does to the siting answer. Moving from transport to DC-OPF, with everything else fixed, shifts capacity toward

offshore and northern nodes. So part of the spread between studies of this kind could come from the grid representation they have in common, independently of the cost and demand assumptions on which they differ. The sensitivity analysis complicates this. The onshore result here holds only above a certain offshore premium; below roughly half the premium assumed in this study, offshore becomes the majority (Section 5.7). Both system studies sit below that crossover: Glaum et al. (2024) assume about a 10% premium and Gea-Bermúdez et al. (2023) close to zero. At those premiums the model here would itself produce an offshore majority. This shows the premium is not what separates the two studies, since the lower-premium study, Gea-Bermúdez et al. (2023), is the one that finds onshore production cheapest. Their onshore result therefore holds despite a low premium, whereas the onshore result here depends on a high one. The two reach the same direction by different routes, which reinforces that assumptions other than the premium, ones this study did not vary, are shaping their conclusions.

Where some studies agree is that the two are not alternatives. Martínez-Gordón et al. (2022) find that offshore electrolysis complements onshore production rather than replacing it, and Löhr et al. (2023) treat the two as points on a capital-versus-operational trade-off rather than as alternatives. The result here is the same: offshore capacity appears as an addition at specific hubs, and not as a replacement. The question is therefore not which of the two wins, but how large the offshore addition is and what determines it. This study also finds that offshore hydrogen and electricity transmission are not substitutes on the cost side. In studies where offshore hydrogen is attractive because it avoids export infrastructure (Glaum et al., 2024; Jang et al., 2022), conversion offshore replaces cable investment. Here both rise together under DC-OPF: offshore electrolyser investment roughly doubles while offshore cable investment also increases (Section 5.3). Congestion raises the value of converting near the wind and of expanding power transmission capacity at the same time, so offshore conversion does not displace transmission infrastructure in this system.

The single-farm studies show the same logic at a smaller scale: the price the electrolyser faces decides where it is built. Chapter 2 showed that their split tracks whether the model lets the electrolyser trade with the grid at market prices. McDonagh et al. (2020) provide the electrolyser grid access at market prices and find onshore preferable. Jang et al. (2022) and Travaglini et al. (2025) isolate the farm from the grid, so the only price the electrolyser sees is local, and find offshore preferable. In each case the location follows from the electricity price the model makes available to the electrolyser. The present study sits one level above this. A single-farm model has no large network on which congestion or flow physics could act, so the grid representation is not relevant choice to make and the price has to come from outside. In this system-level study the electricity price is not an input assumption. It is produced by the network interactions and the grid representation applied to them. A transport model gives almost every node the same price, so locational price differences cannot drive siting. DC-OPF produces real locational prices, the offshore and northern nodes come out cheap, and offshore siting strengthens. The main finding of Chapter 2 on single-farm studies that the available price decides, becomes here that the representation decides, because the representation sets the price.

Two studies reach the same outcome by changing the price the electrolyser faces, rather than the flow physics. Kenis et al. (2024) vary the market design, comparing nodal and zonal pricing. Under nodal pricing a congested export cable strands local offshore supply and lowers the offshore price, which improves offshore electrolyser economics. Lüth et al. (2024) reduce offshore interconnector capacity and find that this raises offshore electrolyser utilisation, because the congestion forces more electricity to be converted locally. Neither changes the electricity flow physics, as this study does. What all three share is the outcome: each produces a low local offshore price in the model, and in each case hydrogen production moves toward the offshore node. The lever differs, the mechanism is the same low offshore price, and the outcome is the same.

This study and Bødal et al. (2024) agree on the central point and differ on the detail. Both find that pipeline flexibility is not the main driver of electrolyser location, and that the outcome is set mainly by the electricity price level and the offshore cost premium. Both also find the main linepacking effect in the 2030 investment pattern rather than in the long-run geography. They differ on what that 2030 effect is. Bødal et al. (2024) find that linepacking brings offshore electrolyser deployment forward into 2030 and raises onshore electrolysis overall. Here linepacking spreads 2030 investment across more onshore nodes and leaves the offshore share slightly lower. Two modelling differences make it difficult to attribute this disagreement to linepacking itself. In Bødal et al. (2024) the onshore electricity

price is an exogenous input, and it is the main driver of their siting outcome: offshore electrolysis is competitive only within a medium price window, where high prices trigger enough offshore wind to leave a local surplus worth converting. Linepacking in their model therefore acts on a price the model does not produce, while here it acts on prices produced by the network representation itself. Their linepacking also resets at each sub-period boundary rather than operating within fixed blocks, which gives it a different temporal shape. Either difference could produce a different 2030 pattern on its own. The agreement between the two studies is the more reliable finding, because it holds despite both differences, while the disagreement cannot be traced to a single cause.

Read together, these comparisons point in one direction. The literature reads as a set of studies reaching different answers about the same system. This study suggests that some of that difference is not about the system at all, but about how the model represents the network that prices it. A study that prices offshore wind low, whether by isolating a farm, by using nodal rather than zonal pricing, or by enforcing flow physics on a fine network, will tend to find offshore production more attractive. The question of where hydrogen should be produced therefore cannot be separated from how the electricity network is modelled. For modellers, the network representation is not a neutral technical choice: a transport or NTC formulation suppresses the locational price differences that move hydrogen production, so a study that uses one will tend to find onshore production. One that prices offshore wind low, by isolating a farm, by pricing the offshore node separately from the onshore zone, or by enforcing flow physics, will tend to find offshore production more attractive. The representation should be chosen and reported as deliberately as the cost and demand assumptions.

6.2. Limitations

This study makes simplifications to keep the model computationally tractable. The ones that matter most are those that could affect the comparison between scenarios, since that comparison is the basis of every finding.

The most important limitation is the use of the fixed network throughout all scenarios. The electricity and hydrogen grids are sized in a preparatory run that uses the transport formulation, without DC-OPF or linepacking physics, and are then held constant across all four scenarios. This choice is made so that differences in results come from the network representation and not from differences in the grid itself. The consequence is that the network on which the scenarios run was not itself optimised under the physics those scenarios apply. The offshore shift under DC-OPF is therefore a response to a grid that was sized without DC-OPF. A grid that would be co-optimised with the flow physics might be more suitable and congestion could reduce which drove the offshore shift. This could reduce the offshore share. This co-optimisation cannot be done within a single linear program, because line capacity and reactance depend on each other, which is the reason the two-step approach was used in the first place.

The same fixed network also partly produces unmet demand served by dummy producers. Part of the activation is a genuine supply shortage, and part of the system stress under DC-OPF comes from the network being frozen rather than from a physical shortage alone. The full year is reduced to four representative weeks, which keeps the problem solvable but cannot represent all situations. This has a larger influence on the unmet demand than on the siting: unmet demand appears only in the single most stressed representative periods, and the weighting then scales that periods to the whole year, so the annual figure depends strongly on how extreme that periods happen to be. The siting decision responds to conditions across all represented hours rather than to a specific period, so it is much less sensitive to which periods the clustering selected. The 2040 dummy activation should therefore be read as the model's representation of system stress under a reduced set of periods, not as a precise count of unmet demand hours. Whether this activation distorts the central siting result is addressed in Section 7.1.

A second group of limitations concerns what the optimiser is allowed to know and value. The model has perfect foresight: when it invests in 2030 it already knows the 2040 demand, costs, and weather. This affects the timing result in particular. Bringing offshore electrolyzers forward to 2030 under DC-OPF assumes the investor in 2030 already anticipates the 2040 congestion. Without seeing that far into the future investments might not build offshore that early. The forward shift in timing should be read as the cost-optimal response under full information, not as a forecast. The model also optimises for system

cost alone. Public acceptance, permitting, spatial planning, and political siting choices play no part, although they strongly shape real offshore and onshore decisions. The locations the model selects are therefore least-cost locations, not predictions of where infrastructure will actually be built.

A third group concerns the hydrogen side. Linepacking is represented as a four-hour temporal resolution approximation rather than through pipeline pressure dynamics, and the flexibility is granted in fixed blocks rather than as free intra-day shifting. The linepacking results should therefore be read as indicating the direction and scale of the effect, not as exact values. A coarser block would give the flexibility more reach, which is examined in Section 7.1. Hydrogen storage is also fixed and identical across all scenarios, and because storage and the well-connected backbone already shift production in time, the linepacking effect cannot be separated cleanly from the flexibility they already supply. The effect reported here is therefore a lower bound on what pipeline flexibility could contribute in a system with less storage. Storage assets are also permitted to charge and discharge in the same timestep. With round-trip losses, this would in principle let the model dissipate surplus energy through storage rather than curtailing it. In this model there is no incentive to do so, because generation can be curtailed directly at no cost, so storage is not needed as a disposal route. It occurs in a small number of timesteps, and because the storage fleet is identical across all four scenarios, any distortion is the same in every scenario and cancels in the comparison. Enforcing mutual exclusivity would require binary variables and turn the model into a MILP.

Another boundary concerns the hydrogen backbone. It is sized in the preparatory optimisation to be largely uncongested, so hydrogen prices carry almost no locational signal in any scenario. Linepacking therefore acts only on operation here. On a more constrained backbone the impact could differ. Pipeline congestion could create hydrogen price differences between locations, so an electrolyser would face two locational price signals at once and cheap electricity would no longer be sufficient on its own. Linepacking could also relieve part of that congestion, since it absorbs peaks within the temporal resolution, which would give it a route to affect siting that it does not have here. This was not tested, since the backbone capacity is a fixed input rather than a varied parameter. The operational-only finding for linepacking is therefore specific to an uncongested backbone.

A further group of limitations concerns the structure of the offshore network. The offshore hubs are the candidate locations for offshore electrolysers, and their positions set the cable and pipeline distances that determine offshore connection costs. These hub locations were found with k-means clustering, which is a heuristic: it does not return the same configuration each time, and the number of hubs was fixed at thirteen on the basis of two distance metrics rather than a unique optimum. A different hub count or layout would change the offshore distances and therefore the offshore investment costs, which could affect how much offshore deployment is cost-optimal. This sensitivity was not tested, so the offshore findings are conditional on the chosen hub configuration. The model also allows OWFs to connect only through hubs, not directly to shore, even though many existing farms are radially connected to shore today. Routing all offshore wind through hubs may favour hub-based offshore conversion more than a model with direct radial connections would. Distance to shore is itself a driver of the onshore-offshore split in the literature, with Travaglini et al. (2025) finding offshore production more attractive at greater distances. Since the hub layout sets those distances here, a different configuration would move the offshore share along the same trade-off. This affects the magnitude of the offshore share rather than its direction, since a different hub layout would change offshore connection costs but not the mechanism that makes the hubs cheap.

The remaining simplifications move absolute cost and capacity levels but do not interact with the representation being tested, so they leave the scenario comparison unaffected. The onshore network is aggregated to one node per NUTS region and spatial variation within regions is averaged out of the and profiles are averaged, which smooths wind and demand variability. This could understate the within-region congestion that DC-OPF is meant to capture. All profiles also use a single weather year (2009 or 2019), so the results reflect one year's wind and demand pattern. A different weather year would change which weeks are extreme and therefore the scarcity results, but the price separation under DC-OPF follows from network topology rather than from a particular year's wind pattern. Finally, several assumptions are applied identically in every scenario and therefore cancel in the comparison: uniform costs per milestone year across the fleet, economic lifetimes set equal to technical lifetimes, the exclusion of reactive power, and the trimming of the last 24 hours of the year to allow clustering

into whole weeks. These affect the absolute cost and capacity levels but not the differences between scenarios, which is what the findings rest on.

Taken together, these limitations bound the findings in a specific way. The direction of the effect is robust: every limitation that affects the offshore share affects its size, not whether DC-OPF moves capacity offshore at all. The mechanism is also robust, since it follows from the flow physics rather than from any single assumption. What is conditional is the magnitude: the offshore share depends on assumptions such as the offshore premium, the fixed network, and the hub layout, and a different choice on any of these would change the number without changing the direction.

6.3. Policy recommendations

The recommendations below follow from the results, they should be interpreted with the limitations in mind. The model optimises for system cost alone, and the scenario outcomes depend on the network representation and on a network that was sized once and then held fixed. The recommendations are therefore drawn from conclusions across all scenarios rather than from any single one. They are offered as model-based guidance for infrastructure planning, not as predictions of where infrastructure will be built.

The most robust finding for planning is that electrolyser deployment is onshore-dominated in every scenario and both milestone years. This holds across both network representations, though the offshore share itself depends on the offshore electrolyser premium and the network size. System-wide planning should expect an onshore-dominated electrolyser fleet, sited at the cheaper northern and coastal nodes where offshore wind reaches land. Offshore electrolysis could be efficient as a targeted addition at specific hubs where delivering wind to onshore demand is constrained. Its cost-optimal scale in this model is modest, and the exact magnitude depends on the network representation and the fixed-grid assumption.

The central finding carries a more structural recommendation. Where hydrogen is produced depends on how the electricity grid is configured, so electrolyser siting and grid expansion cannot be planned in isolation. The two decisions are coupled. A grid plan changes which locations have the lowest system-level costs, which changes where electrolysers are cost-optimal, which changes the load the grid must serve. Treating the electrolyser location decision as separate from grid planning risks siting hydrogen production against a grid that will not be efficient, or building a grid that does not anticipate where conversion will occur. The two should be planned together.

These choices are also hard to undo. An electrolyser fleet and the network built around it stay in place for decades, so the locations chosen first narrow the options that remain later. Making decisions based on the results of a representation that hides the locational signal risks locking in an investment that the detailed representation would not have chosen.

A further recommendation concerns the market design that would price these locations. In this model the electricity cost is resolved at each node, so locational cost differences can drive where an electrolyser is cheapest. A real investor instead sees a market price, and under the zonal market design used in the North Sea region today that price is uniform within a bidding zone. The locational cost differences the siting result depends on are therefore not exposed to whoever decides where to build. An offshore bidding zone (Section 2.1) would price the offshore node separately, so the low offshore price during high-wind periods becomes visible instead of being replaced by the onshore zonal price. This is the same lower offshore price that improves offshore electrolyser economics in Kenis et al. (2024). Onshore, a locational price would expose the congestion-driven differences that a zonal price does not capture. A uniform zonal price gives an electrolyser no reason to avoid nodes where the grid is already under pressure. Electrolysers can then land on congested locations, which can worsen shortages or raise the grid expansion needed to serve the added load. This does not by itself favour offshore. A locational price lets an investor rule out the high-price nodes, as the analysis does, and lets offshore compete where its economics are favourable.

A final recommendation concerns how results of this kind should be interpreted. The siting conclusion of any such model is conditional on its assumptions, and the network representation is one of them, but unlike a cost assumption its effect is rarely tested or reported. A government or company using a model

to inform siting should therefore ask which electricity network representation produced the answer, and treat a transport-based result as one that cannot locational differences. The same applies to the other structural assumptions here: the forward shift of offshore investment into 2030, for instance, is the cost-optimal response under perfect foresight, not necessarily a forecast that offshore capacity will be built that early.

Taken together, these interpretations reframe the literature's disagreement rather than settle it. What looked like conflicting answers about the same system is in part a consequence of how each study represents the network that prices it. The direction of the effect found here is robust: enforcing the flow physics separates locational prices and moves some hydrogen production toward the offshore hubs and northern nodes. Its magnitude is conditional, on the offshore cost premium and on how congested the network turns out to be, both of which are uncertain. The onshore-dominant result should therefore be read as directional, with offshore conversion near the hubs as a possible addition where congestion is severe, not as an exact share. These interpretations rest on the limitations set out above, and the next chapter uses them to answer the research question.

7

Conclusion

7.1. Answer to the research question

This chapter answers the four sub-questions in turn, then uses them to answer the main research question:

How do electricity grid and hydrogen network representations in an energy system model influence the cost-optimal location and configuration of hydrogen production in the North Sea region?

The first sub-question characterised the anticipated techno-economic configuration of the future North Sea energy system. It was addressed through the introduction, the literature review, and the case study. The system is built around a large growth in offshore wind, brought to shore and shared between countries through offshore hubs, an onshore electricity grid, and a hydrogen backbone, alongside continued growth in onshore renewables. Producers, demand, storage, and conversion assets interact within it. Electrolysers draw electricity from the grid to produce hydrogen, and can be sited onshore or offshore. For offshore wind in particular, this creates a choice of carrier: its energy can be brought to shore as electricity and converted onshore, or converted to hydrogen near the wind and moved by pipeline. A few features shape the cost-optimal outcome. Cheap northern generation, offshore wind and Norwegian hydro, needs transportation to demand locations, distributed across coastal and inland consumer regions and industrial clusters in all countries. The network representation influences whether that cheap northern and offshore energy can reach the distributed demand. Where hydrogen should be produced, and therefore which infrastructure carries the energy, is the central system design question this study examines.

The second and third sub-questions established how energy system models represent the electricity grid and the hydrogen network. They were addressed through the literature review, the methodology, and the case study. Models represent the electricity grid at different levels of physical detail: from a simple transport model limited only by line capacity, through transport with losses, to DC-OPF and PTDF formulations that enforce the physics of power flow, and at spatial resolutions from one node per country to fine regional grids. Hydrogen networks are represented from rigid point-to-point pipelines, through temporal balances such as a daily or multi-hour hydrogen balance, to full pipeline pressure dynamics. Among these modelling assumptions, the network representation is a distinct kind of modelling choice. It is not the system boundary, which sets the question, and not an uncertain cost, which a sensitivity analysis can vary. It is a structural feature that decides which physics the model can express. This study isolates one choice on each side. For the electricity grid, transport against DC-OPF, and for the hydrogen network, no linepacking against a four-hour linepacking approximation. All other assumptions are held fixed, so any difference in the cost-optimal siting comes from the representation alone.

The fourth sub-question asked what the cost-optimal siting and configuration are under each representation. The answer has one robust part and one representation-dependent part. The robust part is that hydrogen production is predominantly onshore in every scenario and both milestone years, above 80% throughout, with offshore capacity appearing only as an addition at specific hubs and not as a full

replacement. The highest offshore share anywhere is 18.3%. The representation-dependent part is that moving from the transport model to DC-OPF shifts capacity toward the offshore hubs and northern onshore nodes, brings offshore investments forward in time, and raises the total built. The reason, established in Chapter 5, is that DC-OPF produces a more realistic locational price signal that the transport model does not. Enforcing the flow physics makes cheap northern and offshore power unable to reach interior demand, so those interior nodes become expensive and the cheap northern and offshore nodes draw the investment. The transport model prices almost every node alike, so no such signal exists to move siting. Linepacking, by contrast, changes only how electrolyzers operate within the day, not where they are built.

The four sub-questions together answer the main research question. A network representation influences the cost-optimal location of hydrogen production by determining which locational price signals exist in the first place. Siting follows the locational cost of electricity, so a representation that suppresses locational cost differences cannot produce a locational electricity price reason to site in one place over another, while a representation that admits them can. This is why the electricity grid representation, not the hydrogen network representation, is the decisive choice for where hydrogen should be produced.

The electricity grid representation is decisive because, in this model, it is the only one of the two that produces locational price differences. Under the transport model, power routes freely, so almost every node sees the same price and there is no locational reason to favour one site. Under DC-OPF the flow physics prevent that free routing: cheap northern and offshore generation cannot all reach interior demand, so the cheap nodes and the expensive interior nodes separate in price. Electrolyser siting responds to that separation. This is what produces the changes reported in Chapter 5: moving to DC-OPF shifts capacity toward the offshore hubs and northern nodes, brings it forward so offshore appears already in 2030, and raises the total built by about 15%. It also triggers hydrogen-to-power conversion at the expensive interior nodes, as the opposite mechanism of the electrolyser siting, as a way to serve demand the constrained grid cannot reach.

Offshore electrolysis is a growing addition to a system dominated by onshore electrolysis, not a replacement for it. The reason is the same price landscape that drives the shift. Several northern onshore nodes are about as cheap as the hubs and do not carry the offshore cost premium, so where a cheap onshore node exists it is preferred. The average locational price also acts in one direction only. A high price reliably rules a candidate node out, but a low price does not rule one in. Among the cheap candidates the price no longer orders the outcome, and what decides the placement between them sits below the resolution of the annual prices this study reports.

The hydrogen network representation does not move siting, and the reason completes the picture. The hydrogen backbone stays uncongested in every scenario, so hydrogen prices are almost uniform across nodes. The hydrogen representation therefore has no locational price differences to influence the siting decision, which is why linepacking changes how electrolyzers operate rather than where they are built on the uncongested backbone studied here. Its effect is to let an electrolyser concentrate its electricity use in the cheapest hours within a block, which lowers system operating cost but leaves the investment location nearly unchanged.

This operational character is partly a consequence of the four-hour block. A longer averaging window, such as a full day, would give the flexibility more reach. The electrolyser could concentrate its consumption in a few cheap hours and ignore the expensive rest of the day, behaving more like short-term storage. This is mainly an operational change, but it could in principle reach location as well. A node with a high average price but a few very cheap hours is unattractive to build at when the electrolyser must also run in the surrounding expensive hours, but becomes viable if it can place almost all its consumption in the cheap hours. A wider window could therefore pull such nodes into the cost-optimal siting set. However, two things bound this effect. Hydrogen storage already shifts production across time in every scenario, so part of this reach exists regardless of linepacking, and whether nodes with this particular price shape exist in the system was not tested. The likely effect of a coarser window is therefore still mainly operational, with only a limited and untested potential to change location.

Taken together, these findings answer the research question. The hydrogen network representation influences how hydrogen production operates but not where it is located. The electricity grid representation influences both, and is the decisive choice: it determines whether the locational price differences

that siting responds to exist at all. When both are active the electricity representation dominates, with the combined scenario following the DC-OPF scenario in scale, timing, and location rather than the linepacking scenario. The cost-optimal location of hydrogen production therefore depends more on how the electricity network is represented than on the hydrogen network representation tested here.

Two design choices affect how far this answer can be trusted. The network was sized once under the transport model and then held fixed, the deliberate mechanism that makes the comparison possible (Section 4.5.1). Its consequence is that the DC-OPF congestion driving the offshore shift is measured on a grid not optimised for those flows. The line-capacity sensitivity analysis confirms the effect: the offshore share falls as capacity rises, while onshore dominance holds throughout. The dummy producers do not distort the siting result. They are absent in 2030, and in 2040 supply about 0.2% of energy, concentrated at congested interior nodes that normal-hour prices already rule out for electrolyzers. The exclusion of dummy hours makes those nodes appear cheaper, not more expensive, so it cannot be falsely ruling them out, and the cheap northern and coastal nodes that receive the large investments see almost no dummy activation. The direction of the finding, that the electricity representation moves siting, is therefore robust, while the precise offshore share is conditional on the network size and the offshore premium.

How far this answer can be generalised depends on which parts of it rest on the model setup. The difference in weight between the electricity and hydrogen network representations is partly a product of this system: the hydrogen backbone was sized to be uncongested, so hydrogen carried no locational signal here, and on a constrained backbone the hydrogen network representation could matter more. The onshore dominance is conditional on the offshore cost premium, which sits at the high end of values in literature. What generalises is the mechanism: a representation that produces locational price differences moves siting toward the cheap nodes, and one that suppresses them cannot. That mechanism does not depend on the network sizes or cost levels assumed here, but on whether congestion exists somewhere in the system being modelled.

Beyond the modelling question, the findings carry a system-level insight. Electrolyzers are the bridge between the electricity and hydrogen networks, and in this system the hydrogen side of that bridge is uncongested while the electricity side is not. When this is the case, the cost-optimal place for electrolyzers is at the electricity bottlenecks: where cheap power is stranded, conversion turns it into a carrier that can still move. This also connects the siting question to the offshore wind expansion. A large share of available offshore wind, between a fifth and a quarter in these scenarios, is curtailed. Placing electrolyzers where that wind is stranded converts some of it into hydrogen that can still move, which recovers energy that would otherwise be lost and improves the economic case for the offshore wind projects. Where hydrogen should be produced is therefore not only a cost question for the hydrogen system, it affects how much of a large offshore wind expansion can be used at all. Siting is also a load decision, not only a response to prices: an electrolyzer placed where cheap power is already stranded is served locally, while one placed behind a constrained corridor adds to what that corridor must carry and causes congestion.

7.2. Implications for modelling

The finding that location depends on the electricity grid representation is relevant beyond this case. A model that prices offshore wind low, by whatever method, will tend to find offshore production attractive, and one that does not will not. The answer follows the representation. This is a controlled instance of a general point. Sterman (2002) argues that a model's boundary and structural choices usually shape its results more than its parameters do. Here a parameter, the offshore premium, does move the outcome strongly, but its influence is easily found with a sensitivity analysis. The network representation is a structural choice that stays hidden unless the model is built both ways and compared, as this study does. This places unequal weight on the two representations. For a model whose question is where hydrogen should be produced, the electricity grid representation is the choice that must be made carefully. This does not mean the hydrogen network can be treated casually. Its topology, capacities, and demand still determine where hydrogen can go and at what cost. The flexibility of that network turns out to matter less for where electrolyzers are built. A four-hour linepacking approximation barely changed the long-run location compared to no linepacking on an uncongested backbone, yet full pipeline pressure dynamics were not tested.

7.3. Suggested future research

Three directions for future work follow from this study. Two arise from its most consequential limitations, and one from its approach.

The first is the fixed network, the most consequential limitation. Because the grid was sized under the transport formulation and held constant, the offshore shift is a response to a grid that was never optimised under DC-OPF. A grid co-optimised with the flow physics might reduce some of the congestion that drives offshore conversion, lowering the offshore share. The most valuable next step is therefore to co-optimize the network with the physics it represents. This needs to be done with a method beyond an LP, such as an iterative method that switches between sizing the network and applying the physics. It would test whether the offshore shift survives once the grid can adapt to DC-OPF.

The second is linepacking. Its effect on location was small, but the four-hour block is an approximation of what is physically a pipeline-pressure process, so this result indicates the direction and scale of the effect rather than its exact size. A useful next study would represent linepacking through pressure dynamics and test whether the small effect found here holds under a physical formulation. The size of the effect is also less apparent because hydrogen storage already let the system shift hydrogen in time. A study that varies the storage fleet alongside a pressure-based linepacking representation would separate the two and show how much pipeline flexibility adds on top of the storage a real system would have.

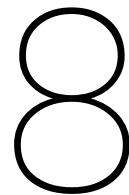
A broader direction follows from the study's own approach. The contribution here was to isolate one structural modelling choice that differs across the literature: the network representation. Isolating other choices one at a time would show how much of the disagreement in the literature each explains. The other differences between studies are not all the same kind of choice, which shapes how each would be tested.

Some are parameters that can be varied within the present model, as the sensitivity analysis did for the offshore premium, demand, and network capacity. HVDC cost and the level of hydrogen demand fall in this group: each is a value, and testing it needs no change to the model structure.

Others concern scope and resolution rather than a value, such as the spatial resolution of the model. This is not a parameter to vary but a choice of how much of the system to resolve, and a finer representation could reveal congestion and siting differences this study cannot.

A third group is structural, like the network representation itself. Relaxing perfect foresight changes the temporal formulation, and moving beyond cost-only optimisation changes the objective. Market design, the choice between nodal, zonal, and offshore bidding zones, is also structural. This has been studied in isolation, but not alongside the network representation in a multi-country model of this kind. Each of these would require rebuilding part of the model rather than changing an input.

The most direct structural extension is to go further along the axis this study already moved on. It compared transport with DC-OPF, and no linepacking with a four-hour approximation, but both DC-OPF and the four-hour block do not include the most realistic network physics. A fuller electricity representation, such as AC power flow, and a physical hydrogen representation based on pipeline pressure dynamics, would test whether the effects found here hold at a higher level of detail. Neither has been applied to North Sea electrolyser siting, so this would not resolve an existing disagreement but would show whether the mechanism identified here survives a more physical formulation.



Reflection

My interest in this topic developed over several years before it became a thesis. My bachelor final project looked at hydrogen networks in the Netherlands. Later courses on offshore energy and the use of ESOMs like Calliope deepened the interest, and courses on linear and mixed-integer linear programming at the Technical University of Munich showed me how widely these methods apply. This thesis is where those threads came together. It let me work on hydrogen and offshore infrastructure with the modelling tools I had been learning to use, on a question large enough to need all of them.

The strongest thing I take from the work is a changed view of what energy system modelling is for. Initially I saw models as machines that produce an answer. The literature got me thinking on that view. Different models reached different conclusions about the same North Sea system, framed their assumptions differently, and did not line up. Setting the studies side by side and asking what modelling assumptions actually do was what eventually changed my thinking. The disagreement was patterned, not random, and much of it traced back to choices that were never tested in isolation. Building the thesis around isolating one such choice taught me that the interpretation of a model matters as much as its output, and that a result means little without the assumptions that produced it. The second lesson was methodological. A real energy system cannot be reproduced, so the work is not about building a perfect simulation. It is about choosing the right question and the right abstractions, and holding onto that question, because without clearly thinking of that, a model of this kind never finishes. Alongside this I learned a large amount of new theory and skills: the Julia language the model is built in, the mathematical formulation of an energy system as a linear program, the economics of electricity pricing, and the physics behind the DC-OPF constraints in real electricity networks.

The thesis also showed me where its own perspective ends. It demonstrates that the siting of hydrogen production is a hard problem and that the choices made now matter for the cost and efficiency of the future system. To really understand the system, research like this can be of value to managers and decision makers. But it reaches this through cost-optimisation alone in this case. Real decisions about where to build electrolyzers and grids also turn on public acceptance, laws and regulations, and national strategic interests, none of which a least-cost model represents. This thesis sits on the engineering and analytical side of the CoSEM spectrum, where it deals systematically with the technical complexity of a multi-country socio-technical system. The actor and institutional side is present in the framing of the problem but not in the method. A fuller treatment would place the least-cost results inside that wider decision space, which is also where the policy recommendations and the cost-only limitation of this study point. Recognising that boundary clearly is itself part of what the programme taught me. The technical answer is one input to a decision, not the decision. That, together with the modelling and interpretation skills the thesis is built on, is valuable knowledge which I will carry on in my future career.

AI statement

I used artificial intelligence tools in several ways during this thesis. After writing the initial text, I used Anthropic Claude and Google Gemini to refine sentences and correct grammar. I also used these tools for structural feedback and Julia and LaTeX coding tips. Gemini Code Assist provided suggestions for writing plotting scripts in Visual Studio Code. I processed all raw in- and output data manually through CSV files without AI assistance. Finally, after reading the literature and writing my own summaries, I used Google NotebookLM to help me check my notes on specific statements and locate them within the sources. After using these tools, I reviewed and edited the content as needed and I take full responsibility for the content of this thesis.

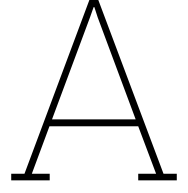
References

- Alghanem, H., & Buckley, A. (2025). Modelling regional solar photovoltaic capacity in Great Britain. <https://doi.org/10.48550/ARXIV.2502.19243>
- Ameli, H., Pudjianto, D., Strbac, G., & Brandon, N. P. (2025). The impact of hydrogen on decarbonisation and resilience in integrated energy systems. *Advances in Applied Energy*, 17, 100200. <https://doi.org/10.1016/j.adapen.2024.100200>
- Aravena, I., L  t  , Q., Papavasiliou, A., & Smeers, Y. (2021). Transmission capacity allocation in zonal electricity markets. *Operations Research*, 69(4), 1240–1255. <https://doi.org/10.1287/opre.2020.2082>
- B  dal, E. F., Holm, S. E., Subramanian, A., Durakovic, G., Pinel, D., Hellemo, L., Ortiz, M. M., Knudsen, B. R., & Straus, J. (2024). Hydrogen for harvesting the potential of offshore wind: A North Sea case study. *Applied Energy*, 357, 122484. <https://doi.org/10.1016/j.apenergy.2023.122484>
- Calado, G., Castro, R., Pires, A., & Marques, M. J. (2024). Assessment of hydrogen-based solutions associated to offshore wind farms: The case of the Iberian Peninsula. *Renewable and Sustainable Energy Reviews*, 192, 114268. <https://doi.org/10.1016/j.rser.2023.114268>
- Cao, K.-K., Pregger, T., Haas, J., & Lens, H. (2021). To prevent or promote grid expansion? Analyzing the future role of power transmission in the European energy system. *Frontiers in Energy Research*, 8, 541495. <https://doi.org/10.3389/fenrg.2020.541495>
- Dawson, N., Fischer, J., Kuhn, M., Pasotti, A., Rouzaud, D., mhugent, Bruy, A., Sutton, T., Dobias, M., Pellerin, M., Rouault, E., Olaya, V., Blottiere, P., Macho, W., Blazek, R., Bartoletti, L., Sherman, G., Sant-anna, H., Cabieces, J., ... Jurgiel, B. (2026, May 1). *qgis/QGIS: 4.0.2* (Version final-4_0_2). Zenodo. <https://doi.org/10.5281/ZENODO.19949287>
- Delft High Performance Computing Centre (DHPC). (2026). DelftBlue Supercomputer (Phase 1). <https://www.tudelft.nl/dhpc/ark:/44463/DelftBluePhase2>
- Electric Power Research Institute. (2025, December). *Comparing open-source integrated planning models in 2025* (No. 3002033187). EPRI.
- Elia Group. (2023, January 1). Belgi   - Elektrische Hoogspanningsnetten (70 tot 380 kV). <https://www.elia.be/-/media/project/elia/elia-site/infra-and-projects/our-infra/map-of-the-high-voltage-grid-2023.pdf>
- Energy Ministers of the North Seas Countries. (2023, April 24). Ostend Declaration of Energy Ministers. <https://www.government.nl/documents/diplomatic-statements/2023/04/24/ostend-declaration-on-the-north-sea-as-europes-green-power-plant>
- Epstein, J. M. (2008). Why model? *Journal of Artificial Societies and Social Simulation*, 11(4), 12. <https://www.jasss.org/11/4/12.html>
- European Commission. (n.d.). *Hydrogen* [Energy]. Retrieved March 26, 2026, from https://energy.ec.europa.eu/topics/eus-energy-system/hydrogen_en
- European Commission. (2019, November 12). *The European Green Deal* (COM(2019) 640 final). European Commission. https://eur-lex.europa.eu/resource.html?uri=cellar:b828d165-1c22-11ea-8c1f-01aa75ed71a1.0002.02/DOC_1&format=PDF
- European Commission. (2020, November 19). *An EU strategy to harness the potential of offshore renewable energy for a climate neutral future* (COM(2020) 741 final). European Commission. <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020DC0741>
- European Commission. (2022, May 18). *REPowerEU plan* (COM(2022) 230 final). European Commission. https://eur-lex.europa.eu/resource.html?uri=cellar:fc930f14-d7ae-11ec-a95f-01aa75ed71a1.0001.02/DOC_1&format=PDF
- European Hydrogen Backbone. (2021a, April). *Extending the European Hydrogen Backbone*. Guidehouse. <https://ehb.eu/files/downloads/European-Hydrogen-Backbone-April-2021-V3.pdf>
- European Hydrogen Backbone. (2021b, June). *Analysing future demand, supply and transport of hydrogen*. Guidehouse. <https://ehb.eu/files/downloads/EHB-Analysing-the-future-demand-supply-and-transport-of-hydrogen-June-2021-v3.pdf>

- European Hydrogen Backbone. (2023, November). *Implementation Roadmap - cross border projections and costs update*. Guidehouse. <https://ehb.eu/files/downloads/EHB-2023-20-Nov-FINAL-design.pdf>
- European Hydrogen Backbone. (2025). Hydrogen Infrastructure Map. <https://www.h2inframap.eu/#map>
- European Marine Observation and Data Network. (2024). EMODnet Digital Bathymetry (DTM). <https://emodnet.ec.europa.eu/geoviewer/>
- European Network of Transmission System Operators for Electricity. (2024, January). *Offshore network development plans 2024: European offshore network transmission infrastructure needs - pan-European summary*. ENTSO-E. https://eepublicdownloads.blob.core.windows.net/public-cdn-container/tyndp-documents/ONDP2024/web_entso-e_ONDP_PanEU_240226.pdf
- European Network of Transmission System Operators for Electricity. (2025, September 4). *Opportunities for a more efficient European power system by 2050 - infrastructure gaps report*. ENTSO-E. https://eepublicdownloads.blob.core.windows.net/public-cdn-container/tyndp-documents/TYNDP2024/foropinion/Infrastructure_Gaps_Report.pdf
- European Network of Transmission System Operators for Electricity. (2026). Transparency platform. <https://transparency.entsoe.eu/>
- European Network of Transmission System Operators for Electricity and Gas. (2024). TYNDP 2024 scenarios. <https://2024.entsoe-tyndp-scenarios.eu/download/>
- Eurostat. (2021). Territorial units for statistics (NUTS). <https://ec.europa.eu/eurostat/web/gisco/geodata/statistical-units/territorial-units-statistics>
- Farahmand, H., Günther, S. H., & Kristiansen, M. (2024). Evaluating the offshore wind business case and green hydrogen production: A case study of a future North Sea Offshore Grid. *Electric Power Systems Research*, 234, 110814. <https://doi.org/10.1016/j.epsr.2024.110814>
- Fattahi, A., Sánchez Diéguez, M., Sijm, J., Morales España, G., & Faaij, A. (2021). Measuring accuracy and computational capacity trade-offs in an hourly integrated energy system model. *Advances in Applied Energy*, 1, 100009. <https://doi.org/10.1016/j.adapen.2021.100009>
- Gao, Z., Gazzani, M., Tejada-Arango, D. A., Soares Siqueira, A., Wang, N., Gibescu, M., & Morales-España, G. (2025). Fully flexible temporal resolution for energy system optimization. *Applied Energy*, 396, 126267. <https://doi.org/10.1016/j.apenergy.2025.126267>
- Gea-Bermúdez, J., Bramstoft, R., Koivisto, M., Kitzing, L., & Ramos, A. (2023). Going offshore or not: Where to generate hydrogen in future integrated energy systems? *Energy Policy*, 174, 113382. <https://doi.org/10.1016/j.enpol.2022.113382>
- Glaum, P., Neumann, F., & Brown, T. (2024). Offshore power and hydrogen networks for Europe's North Sea. *Applied Energy*, 369, 123530. <https://doi.org/10.1016/j.apenergy.2024.123530>
- Global Energy Monitor. (2026, February). Global Wind Power Tracker. <https://globalenergymonitor.org/projects/global-wind-power-tracker>
- Gotzens, F., Heinrichs, H., Hörsch, J., & Hofmann, F. (2019). Performing energy modelling exercises in a transparent way - the issue of data quality in power plant databases. *Energy Strategy Reviews*, 23, 1–12. <https://doi.org/10.1016/j.esr.2018.11.004>
- Hagspiel, S., Jägemann, C., Lindenberger, D., Brown, T., Cherevatskiy, S., & Tröster, E. (2014). Cost-optimal power system extension under flow-based market coupling. *Energy*, 66, 654–666. <https://doi.org/10.1016/j.energy.2014.01.025>
- Hardy, S., Themelis, A., Yamamoto, K., Ergun, H., & Van Hertem, D. (2023). Optimal grid layouts for hybrid offshore assets in the North Sea under different market designs. *IEEE Transactions on Energy Markets, Policy and Regulation*, 1(4), 468–479. <https://doi.org/10.1109/TEMPR.2023.3289582>
- Hartvig, M., Douwes, M., & Ea Energy Analyses A/S. (2025, February 27). Pathway 2.0 output data (annual). <https://doi.org/10.5281/ZENODO.14939154>
- Hatton, L., Johnson, N., Dixon, L., Mosongo, B., De Kock, S., Marquard, A., Howells, M., & Staffell, I. (2024). The global and national energy systems techno-economic (GNESTE) database: Cost and performance data for electricity generation and storage technologies. *Data in Brief*, 55, 110669. <https://doi.org/10.1016/j.dib.2024.110669>
- Hystories. (2022, February 18). *Assumptions and input parameters for modelling of the European energy system* (No. D5.4-0). https://hystories.eu/wp-content/uploads/2022/05/Hystories_D5.4-0-Assumptions-and-input-parameters-for-modelling-of-the-European-energy-system.pdf

- International Energy Agency. (2025, September 12). *Global Hydrogen Review 2025*. IEA. <https://www.iea.org/reports/global-hydrogen-review-2025>
- International Hydrographic Organization. (1953). *Limits of oceans and seas* (3rd ed.). Imp. Monegasque.
- Jang, D., Kim, K., Kim, K.-H., & Kang, S. (2022). Techno-economic analysis and Monte Carlo simulation for green hydrogen production using offshore wind power plant. *Energy Conversion and Management*, 263, 115695. <https://doi.org/10.1016/j.enconman.2022.115695>
- Jottrand, S., & Hendrick, P. (2025). Parametric study for cost optimization of hydrogen pipelines in time varying conditions. *Energy*, 337, 138608. <https://doi.org/10.1016/j.energy.2025.138608>
- Kenis, M., Dvorkin, V., Schittekatte, T., Bruninx, K., Delarue, E., & Botterud, A. (2024). Evaluating offshore electricity market design considering endogenous infrastructure investments: Zonal or nodal? *IEEE Transactions on Energy Markets, Policy and Regulation*, 2(4), 476–487. <https://doi.org/10.1109/TEMPR.2024.3399611>
- Klatzer, T., Bachhiesl, U., & Wogrin, S. (2022). State-of-the-art expansion planning of integrated power, natural gas, and hydrogen systems. *International Journal of Hydrogen Energy*, 47(47), 20585–20603. <https://doi.org/10.1016/j.ijhydene.2022.04.293>
- lisazeyen, HAMPP, J., Neumann, F., Parzen, M., aalamia, Franken, L., Brown, T., Geis, J., Finozzi, F., Glaum, P., Lerede, D., martavp, Millinger, M., Schledorn, A., Gilon, T., TomKae00, Trippe, L., Toni, cpschau, ... s8au. (2026, March 18). *PyPSA/technology-data: v0.14.0-2020-v2* (Version v0.14.0-2020-v2). Zenodo. <https://doi.org/10.5281/ZENODO.3994163>
- Löhr, L., Lambriex, C., Kampmann, C., & Moser, A. (2023). Model-based assessment of design principles for the green hydrogen production in the North Sea. *2023 19th International Conference on the European Energy Market (EEM)*, 1–6. <https://doi.org/10.1109/EEM58374.2023.10161943>
- Lüth, A., Werner, Y., Egging-Bratseth, R., & Kazempour, J. (2024). Electrolysis as a flexibility resource on energy islands: The case of the North Sea. *Energy Policy*, 185, 113921. <https://doi.org/10.1016/j.enpol.2023.113921>
- Martínez-Gordón, R., Gusatu, L., Morales-España, G., Sijm, J., & Faaij, A. (2022). Benefits of an integrated power and hydrogen offshore grid in a net-zero North Sea energy system. *Advances in Applied Energy*, 7, 100097. <https://doi.org/10.1016/j.adapen.2022.100097>
- McDonagh, S., Ahmed, S., Desmond, C., & Murphy, J. D. (2020). Hydrogen from offshore wind: Investor perspective on the profitability of a hybrid system including for curtailment. *Applied Energy*, 265, 114732. <https://doi.org/10.1016/j.apenergy.2020.114732>
- Montes, A., Fournely, D., Sørensen, J. N., & Larsen, G. C. (2025). Techno-economic modeling of floating wind farms. *Energies*, 18(4), 967. <https://doi.org/10.3390/en18040967>
- National Energy System Operator. (n.d.). Potential electricity storage routes to 2050. Retrieved April 15, 2026, from <https://www.neso.energy/document/273166/download>
- Neustroev, G., Tejada-Arango, D. A., Morales-España, G., & Weerd, M. M. d. (2025, December 18). Hull clustering with blended representative periods for energy system optimization models. <https://doi.org/10.48550/arXiv.2508.21641>
- Nieuwenhout, C. (2022). Dividing the sea into small bidding zones? The legal challenges of connecting offshore wind farms to multiple countries. *Journal of Energy & Natural Resources Law*, 40(3), 315–335. <https://doi.org/10.1080/02646811.2021.2011034>
- North Sea Wind Power Hub. (2024, June 24). *Pathway Study 2.0*.
- North Seas Energy Cooperation. (2025, October 23). Timelines-DB. <https://noordzeeloket.nl/en/news/news/2026/new-database-maps-planned-offshore-wind-farms/>
- Pfenniger, S., & Staffell, I. (2016). Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. *Energy*, 114, 1251–1265. <https://doi.org/10.1016/j.energy.2016.08.060>
- Plazas-Niño, F., Ortiz-Pimiento, N., & Montes-Páez, E. (2022). National energy system optimization modelling for decarbonization pathways analysis: A systematic literature review. *Renewable and Sustainable Energy Reviews*, 162, 112406. <https://doi.org/10.1016/j.rser.2022.112406>
- Sánchez Diéguez, M., Fattahi, A., Sijm, J., Morales España, G., & Faaij, A. (2022). Linear programming formulation of a high temporal and technological resolution integrated energy system model for the energy transition. *MethodsX*, 9, 101732. <https://doi.org/10.1016/j.mex.2022.101732>

- Sargent, P., & Sargent, M. (2025). Linepack flexibility for hydrogen and natural gas pipes: A new flexibility metric for energy systems modelling. *International Journal of Hydrogen Energy*, 132, 139–142. <https://doi.org/10.1016/j.ijhydene.2025.04.197>
- Soares Siqueira, A., Tejada-Arango, D. A., Morales-España, G., Neustroev, G., Kiviluoma, J., Clisby, L., Elgersma, M., Wang, N., Ali, S., & Gao, Z. (2026, March 4). *Tulipa Energy Model* (Version v0.21.0). Zenodo. <https://doi.org/10.5281/ZENODO.8363262>
- Staffell, I., & Pfenninger, S. (2016). Using bias-corrected reanalysis to simulate current and future wind power output. *Energy*, 114, 1224–1239. <https://doi.org/10.1016/j.energy.2016.08.068>
- Sterman, J. D. (2002). All models are wrong: Reflections on becoming a systems scientist. *System Dynamics Review*, 18(4), 501–531. <https://doi.org/10.1002/sdr.261>
- Süsser, D., Ceglaz, A., Gaschnig, H., Stavrakas, V., Flamos, A., Giannakidis, G., & Lilliestam, J. (2021). Model-based policymaking or policy-based modelling? How energy models and energy policy interact. *Energy Research & Social Science*, 75, 101984. <https://doi.org/10.1016/j.erss.2021.101984>
- Travaglini, R., Frowijn, L., Bianchini, A., Lukszo, Z., & Bruninx, K. (2025). Offshore or onshore hydrogen production? A critical analysis on costs and operational considerations for the Dutch North Sea. *Applied Energy*, 397, 126290. <https://doi.org/10.1016/j.apenergy.2025.126290>
- Wang, N., & Morales-España, G. (2025, May 1). Vintage-based formulations in multi-year investment modelling for energy systems. <https://doi.org/10.48550/arXiv.2505.00379>
- Wang, N., & Tejada-Arango, D. A. (2025, April 30). Discounting approaches in multi-year investment modelling for energy systems. <https://doi.org/10.48550/arXiv.2504.21709>
- Xiong, B., Fioriti, D., Neumann, F., Riepin, I., & Brown, T. (2025). Modelling the high-voltage grid using open data for Europe and beyond. *Scientific Data*, 12(1), 277. <https://doi.org/10.1038/s41597-025-04550-7>



Mathematical Formulation

A.1. Discounting and annualisation factors

This appendix provides the full expressions for the discounting and annualisation factors referenced in the objective function. The economic representation follows Wang and Tejada-Arango (2025).

The annualisation and discounting factor for investment costs combines a present value discount with a salvage value correction. The present value term discounts costs to the reference year $p^{\text{disc year}}$ using the social discount rate $p^{\text{soc dr}}$. The salvage value correction reduces the effective cost when an asset's economic lifetime extends beyond the final milestone year, preventing the model from fully charging investment costs whose benefits extend beyond the horizon:

$$p_{a,y}^{\text{disc inv}} = \frac{1}{(1 + p^{\text{soc dr}})^{y - p^{\text{disc year}}}} \left(1 - \frac{p_{a,y}^{\text{salvage}}}{p_{a,y}^{\text{inv cost}}} \right) \quad \forall a \in A_y^{\text{inv}}, y \in Y \quad (\text{A.1})$$

The salvage value $p_{a,y}^{\text{salvage}}$ is derived from the annualised investment cost and sums the discounted annual payments over the remaining economic lifetime of the asset that extends beyond the final milestone year:

$$p_{a,y}^{\text{salvage}} = p_{a,y}^{\text{ann inv cost}} \sum_{i=y^{\text{last}}+1}^{y+p_{a,y}^{\text{econ lt}}-1} \frac{1}{(1 + p_{a,y}^{\text{tech dr}})^{i-y}} \quad \forall a \in A_y^{\text{inv}}, y \in Y \quad (\text{A.2})$$

The annualised investment cost converts the costs to an equivalent annual payment, which depends on the technology-specific discount rate $p_{a,y}^{\text{tech dr}}$ and the economic lifetime $p_{a,y}^{\text{econ lt}}$:

$$p_{a,y}^{\text{ann inv cost}} = \frac{p_{a,y}^{\text{tech dr}}}{(1 + p_{a,y}^{\text{tech dr}}) \cdot \left(1 - \frac{1}{(1 + p_{a,y}^{\text{tech dr}})^{p_{a,y}^{\text{econ lt}}}} \right)} \cdot p_{a,y}^{\text{inv cost}} \quad \forall a \in A_y^{\text{inv}}, y \in Y \quad (\text{A.3})$$

The same three expressions apply to transport flows, with asset index a replaced by flow index f and set A_y^{inv} replaced by F_y^{inv} :

$$p_{f,y}^{\text{disc inv}} = \frac{1}{(1 + p^{\text{soc dr}})^{y - p^{\text{disc year}}}} \left(1 - \frac{p_{f,y}^{\text{salvage}}}{p_{f,y}^{\text{inv cost}}} \right) \quad \forall f \in F_y^{\text{inv}}, y \in Y \quad (\text{A.4})$$

$$p_{f,y}^{\text{salvage}} = p_{f,y}^{\text{ann inv cost}} \sum_{i=y^{\text{last}}+1}^{y+p_{f,y}^{\text{econ lt}}-1} \frac{1}{(1 + p_{f,y}^{\text{tech dr}})^{i-y}} \quad \forall f \in F_y^{\text{inv}}, y \in Y \quad (\text{A.5})$$

$$p_{f,y}^{\text{ann inv cost}} = \frac{p_{f,y}^{\text{tech dr}}}{\left(1 + p_{f,y}^{\text{tech dr}}\right) \cdot \left(1 - \frac{1}{(1 + p_{f,y}^{\text{tech dr}})^{p_{f,y}^{\text{econ lt}}}}\right)} \cdot p_{f,y}^{\text{inv cost}} \quad \forall f \in F_y^{\text{inv}}, y \in Y \quad (\text{A.6})$$

The operational cost discounting factor applies to both fixed and variable operational costs. Unlike the investment factor, no annualisation is required since these costs are already expressed as annual values. Instead, $p_y^{\text{disc op}}$ sums the present value discount factor over all years from milestone year y up to the next milestone year, reflecting that each milestone year represents a range of actual years:

$$p_y^{\text{disc op}} = \sum_{y'=y}^{\text{next}(y)-1} \frac{1}{(1 + p^{\text{soc dr}})^{y' - p^{\text{disc year}}}} \quad \forall y \in Y \quad (\text{A.7})$$

For the final milestone year the sum contains only year y itself. In this study both the social and technology-specific discount rates are set to 0.05 uniformly, and $p^{\text{disc year}}$ is set to 2030.

A.2. Storage cycling constraints

The storage balance constraints in Section 3.3.3 require a value for the storage level preceding the first timestep of each period. Since no initial storage level is defined in this study, a cycling condition is applied in which the storage level at the end of the period is used as this preceding value. This holds the net energy change over the period to zero.

The rep-period cycling constraint applies this condition within each representative period for non-seasonal storage assets. It is the storage balance evaluated at the first timestep, with the level of the last timestep used as the preceding value:

$$v_{a,k,t_k^{\text{first}}}^{\text{storage}} = v_{a,k,t_k^{\text{last}}}^{\text{storage}} + p_{t_k^{\text{first}}}^{\text{dur}} \cdot \left(p_{a,y}^{\text{eff in}} \cdot \sum_{f \in F_{a,y}^{\text{in}}} v_{f,k,t_k^{\text{first}}}^{\text{flow}} - \frac{1}{p_{a,y}^{\text{eff out}}} \cdot \sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k^{\text{first}}}^{\text{flow}} \right) \quad (\text{A.8})$$

$$\forall a \in A^{\text{s}} \setminus A^{\text{ss}}, y \in Y, k \in K$$

The inter-period cycling constraint applies the same principle across the full timeframe for seasonal storage assets, using the inter-period storage level of the last period as the value preceding the first period:

$$v_{a,p_y^{\text{first}}}^{\text{storage ip}} = v_{a,p_y^{\text{last}}}^{\text{storage ip}} + \sum_{k \in K} p_{p_y^{\text{first}},k}^{\text{map}} \cdot \sum_{t_k \in T_k} p_{t_k}^{\text{dur}} \cdot \left(p_{a,y}^{\text{eff in}} \cdot \sum_{f \in F_{a,y}^{\text{in}}} v_{f,k,t_k}^{\text{flow}} - \frac{1}{p_{a,y}^{\text{eff out}}} \cdot \sum_{f \in F_{a,y}^{\text{out}}} v_{f,k,t_k}^{\text{flow}} \right) \quad (\text{A.9})$$

$$\forall a \in A^{\text{ss}}, y \in Y$$

In both constraints the net energy exchanged during the period is computed from the same flow terms as the corresponding storage balance, so the cycling condition introduces no new parameters.

B

Input Parameters

This appendix reports the techno-economic parameters for the assets and connections that the model invests in or dispatches. Investment and fixed costs are given for the investable assets and for transport connections. The producer and storage fleets are not investable in this study and are identical across all four scenarios, so only their operational costs and efficiencies are reported here, since these are what affect dispatch. Their investment and fixed costs are taken directly from the sources in Table 4.1. Every asset in the model carries further parameters beyond those listed here. For the non-investable assets, most of these enter the objective function as fixed terms that are identical across scenarios and therefore do not affect the comparison.

Table B.1: Techno-economic parameters for the conversion assets, by milestone year. All conversion assets are investable. The offshore electrolyser investment cost is about 58% above the onshore cost in 2030 and 78% in 2040, which is the offshore cost premium varied in the sensitivity analysis (Section 5.7).

Conversion	Year	Investment cost (EUR/MW)	Fixed cost (EUR/MW/yr)	Operational cost (EUR/MWh)	Efficiency (p.u.)	Lifetime (years)	Source
Electrolyser Offshore	2030	1 420 000	35 500	0	0.72	25	(Hartvig et al., 2025)
	2040	1 190 000	29 750	0	0.72	25	
	2050	1 060 000	26 430	0	0.72	25	
Electrolyser Onshore	2030	900 000	22 500	0	0.72	25	(Hartvig et al., 2025)
	2040	670 000	16 750	0	0.72	25	
	2050	530 000	13 330	0	0.72	25	
Hydrogen CCGT	2030	558 000	20 646	2.11	0.60	30	(Hystories, 2022)
	2040	554 000	19 944	2.06	0.61	30	
	2050	550 000	19 800	2.02	0.61	30	
Hydrogen gas turbine	2030	386 000	11 580	2.10	0.37	25	(Hystories, 2022)
	2040	383 000	11 490	2.10	0.39	25	
	2050	380 000	11 400	2.10	0.40	25	
Fuel cell	2030	3 090 000	46 350	1.04	0.68	20	(Hystories, 2022)
	2040	2 871 000	43 065	1.04	0.68	20	
	2050	2 668 000	40 020	1.04	0.69	20	

Table B.2: Techno-economic parameters for transport connections, by milestone year. Costs are per MW per kilometre of connection length. Transport flows carry no operational cost. The hydrogen pipeline costs are a weighted average of repurposed and newly built pipeline, at 69 and 31 percent respectively, following the share reported by EHB (2021a) (Section 4.2.3).

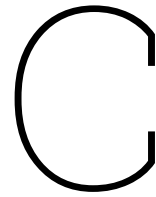
Transport	Year	Investment cost (EUR/MW/km)	Fixed cost (EUR/MW/km/yr)	Lifetime (years)	Source
HVDC (offshore)	2030	2 073	31.10	30	(Hartvig et al., 2025)
	2040	2 011	30.17	30	
	2050	1 955	29.33	30	
HVAC (onshore)	2030	1 161	17.42	30	(Hartvig et al., 2025)
	2040	1 126	16.89	30	
	2050	1 095	16.43	30	
Hydrogen pipeline offshore	2030	663	11.00	30	(Hartvig et al., 2025)
	2040	644	11.00	30	
	2050	626	10.00	30	
Hydrogen pipeline onshore	2030	255	3.00	30	(Hartvig et al., 2025)
	2040	247	3.00	30	
	2050	240	3.00	30	

Table B.3: Operational cost of producer assets by milestone year, in EUR/MWh. These values combine fuel cost, emission factor, carbon price, and variable operating cost as described in Section 4.3.1, and are derived from Hystories (2022), Hatton et al. (2024), Iisazeyen et al. (2026), and the TYNDP carbon prices (ENTSO-E & ENTSG, 2024).

Producer	Operational cost (EUR/MWh)		
	2030	2040	2050
Solar PV	0	0	0
Offshore wind	5.00	4.00	4.00
Onshore wind	0.20	0.20	0.20
Hydro run-of-river	0	0	0
Hydro reservoir	0	0	0
Biomass and waste	77.97	92.61	101.54
Gas biogas combustion engine	147.94	130.71	116.10
Gas steam turbine	94.40	108.86	116.23
Oil	192.68	213.76	224.63
Coal	118.66	144.47	160.21
Nuclear	11.87	12.07	12.27

Table B.4: Operational cost and round-trip efficiency of storage assets, from Hystories (2022). These values are constant across milestone years. Storage assets are not investable in this study, so their investment and fixed costs do not affect the scenario comparison.

Storage technology	Operational cost (EUR/MWh)	Round-trip efficiency (p.u.)
Batteries	0	0.95
Pumped hydro storage	0	0.80
Hydrogen salt caverns	3.03	1.00
Hydrogen depleted field	4.61	0.97
Hydrogen pressure tanks	1.20	1.00



Verification and Validation

This appendix reports the verification and validation checks summarised in Section 3.4. Verification confirms the model calculates as intended. Validation confirms its outputs are physically and economically plausible.

C.1. Verification

C.1.1. Energy balance

This check confirms the model conserves energy. For each scenario and milestone year, the annual electricity and hydrogen balances must close to zero, with energy removed only through the storage losses and conversion efficiencies which are defined explicitly. Across all four scenarios and both milestone years the largest residual is about $6e-7$ MWh against annual flows of order $1e8$ to $1e9$ MWh, which is solver round-off. A finer check confirms the hydrogen-to-electricity ratio equals the conversion efficiency at every node and timestep with production, including under the four-hour blocks.

This verification check confirms that the model conserves energy. For each scenario and milestone year, the annual sum of all electricity flows and all hydrogen flows must close to zero. Energy is removed only through the storage losses and conversion efficiencies that the model defines explicitly, and is created only by producer assets.

The electricity balance is defined such that:

$$\begin{aligned} &\text{Production} + \text{H}_2\text{-to-power output} + \text{Electricity dummy} + \text{Storage discharge} \\ &- \text{Electricity demand} - \text{Electrolyser input} - \text{Storage charge} = 0 \end{aligned} \quad (\text{C.1})$$

The hydrogen balance requires:

$$\begin{aligned} &\text{Electrolyser output} + \text{Storage discharge} \\ &- \text{Hydrogen demand} - \text{H}_2\text{-to-power input} - \text{Storage charge} = 0 \end{aligned} \quad (\text{C.2})$$

Both balances are evaluated over the full year of 8736 hours, with representative period weights applied. Across all four scenarios and both milestone years the largest residual of either balance is about $6e-7$ MWh, against annual flows of order $1e8$ to $1e9$ MWh. The residual is around fourteen to fifteen orders of magnitude smaller than the quantities being balanced, which is the level of numerical round-off in the solver.

Storage losses do not appear as a separate term. The balance accounts for charging and discharging separately, so the round-trip loss is the difference between the two. This loss is supplied by additional production, and the balance still closes, so no correction term is needed.

A finer check was applied to the electrolysis. The ratio of hydrogen output to electricity input was computed for every node and every timestep or block with production. It equals the conversion efficiency

in each case, including the linepacking scenarios where hydrogen is resolved in four-hour blocks. This confirms that the conversion balance holds at the timestep level, not only in the annual aggregate, and that the four-hour block formulation does not distort the conversion.

Table C.1: Complete electricity and hydrogen energy balances by scenario and milestone year (MWh). The energies are in absolute values, and the headers define their positive or negative role in the balance. The residual accounts for solver precision tolerances.

Electricity Balance

Scen.	Year	+ Prod.	+ H2Pow	+ Dum.	+ StorOut	– Dem.	– ElecIn	– StorIn	= Resid.
PS	2030	2.22×10^9	0	0	8.27×10^7	2.03×10^9	1.79×10^8	9.68×10^7	-1.79×10^{-7}
PS	2040	3.29×10^9	0	6.59×10^6	1.40×10^8	2.80×10^9	4.88×10^8	1.57×10^8	3.87×10^{-7}
S1	2030	2.22×10^9	0	0	7.52×10^7	2.03×10^9	1.79×10^8	8.77×10^7	7.45×10^{-8}
S1	2040	3.29×10^9	0	6.59×10^6	1.15×10^8	2.80×10^9	4.88×10^8	1.31×10^8	4.92×10^{-7}
S2	2030	2.23×10^9	1.24×10^7	0	7.71×10^7	2.03×10^9	2.07×10^8	8.99×10^7	3.73×10^{-7}
S2	2040	3.34×10^9	2.70×10^7	6.95×10^6	1.39×10^8	2.80×10^9	5.55×10^8	1.56×10^8	-2.38×10^{-7}
S3	2030	2.22×10^9	0	0	7.84×10^7	2.03×10^9	1.79×10^8	9.20×10^7	-1.04×10^{-7}
S3	2040	3.29×10^9	0	6.46×10^6	1.35×10^8	2.80×10^9	4.87×10^8	1.52×10^8	2.38×10^{-7}
S4	2030	2.23×10^9	1.30×10^7	0	7.62×10^7	2.03×10^9	2.08×10^8	8.91×10^7	4.77×10^{-7}
S4	2040	3.34×10^9	3.03×10^7	6.81×10^6	1.34×10^8	2.80×10^9	5.64×10^8	1.51×10^8	1.19×10^{-7}

Hydrogen Balance

Scen.	Year	+ ElecOut	+ StorOut	– Dem.	– H2Pow	– StorIn	= Resid.
PS	2030	1.29×10^8	1.22×10^7	1.28×10^8	0	1.28×10^7	1.47×10^{-7}
PS	2040	3.51×10^8	8.51×10^7	3.50×10^8	0	8.62×10^7	4.47×10^{-8}
S1	2030	1.29×10^8	1.22×10^7	1.28×10^8	0	1.28×10^7	8.38×10^{-8}
S1	2040	3.51×10^8	8.51×10^7	3.50×10^8	0	8.62×10^7	5.96×10^{-8}
S2	2030	1.49×10^8	1.66×10^7	1.28×10^8	2.07×10^7	1.67×10^7	1.30×10^{-8}
S2	2040	4.00×10^8	8.47×10^7	3.50×10^8	4.43×10^7	9.00×10^7	8.94×10^{-8}
S3	2030	1.29×10^8	8.79×10^6	1.28×10^8	0	9.51×10^6	-4.66×10^{-8}
S3	2040	3.51×10^8	8.31×10^7	3.50×10^8	0	8.37×10^7	4.47×10^{-8}
S4	2030	1.50×10^8	1.49×10^7	1.28×10^8	2.16×10^7	1.50×10^7	-5.59×10^{-8}
S4	2040	4.06×10^8	8.32×10^7	3.50×10^8	4.98×10^7	8.91×10^7	5.66×10^{-7}

C.1.2. Identical fixed network and preparatory run reproduction

The second check confirms that the two-step setup worked and that S1 is a valid base case for the comparison. The base case applies the transport model to the same network as found optimal in the preparatory run, so it should reproduce that run apart from investments. It does. Production, demand, and electrolyser flows match in both milestone years, and dummy activation matches as well: zero in 2030 and 6.59e6 MWh in 2040, identical in location, timing, and quantity at every node and timestep. The fixed onshore network is identical across the four scenarios, so any difference between scenarios comes from the network representation, not from the onshore grid capacities.

C.1.3. Marginal price consistency

The nodal prices are corrected duals of the consumer balance constraint (Equation (3.16)). This check confirms the correction against a known reference. Where a single producer is partially dispatching in a given hour, that unit is marginal and sets the nodal price at its own operational cost, if the local grid is uncongested and no storage influences the nodal price. The corrected dual at that node and hour should then equal that operational cost.

The check uses node DE40, where a CCGT is the marginal unit and the transport flow duals on all connecting lines are zero. In 2030 (S1, representative period 1, hour 110) the raw dual is 7244.12. Dividing by the representative period weight of 12.82, the discount factor of 8.786, and the 1-hour duration gives 64.32 EUR/MWh, which equals the 2030 CCGT operational cost of 64.32 EUR/MWh. In 2040 (S1, representative period 4, hour 119) the raw dual is 318.28. The same correction with the 2040 discount factor of 0.744 gives 74.85 EUR/MWh, against the CCGT operational cost of 74.84 EUR/MWh in 2040, a difference within rounding.

The two points use different milestone years with different discount factors, and the correction recovers the right price in both. The model therefore prices nodes at marginal cost where a clean reference exists, where no other factors influence the nodal price. It confirms that the correction, which removes the representative period weight, the duration, and the discount factor, is applied correctly. At other nodes the price could also reflect binding lines and storage coupling, which the network results in Section 5.5 examine.

C.2. Validation

C.2.1. Capacity utilisation

The electrolyser capacity factor, defined in Equation (3.23), checks whether the cost-optimal fleet operates at a realistic utilisation.

The factor is not a fixed input. It is the utilisation the optimiser chose for the capacity it decided to build. A cost-optimal flexible electrolyser should run at partial load, drawing power when electricity is cheap and backing off when it is expensive. A capacity factor near 1.0 would indicate inflexible baseload operation, and a factor near zero would indicate stranded investment. A value between these extremes is the expected result.

Table C.2: Installed capacity, output metrics, and capacity factors by scenario and milestone year.

Scen.	Year	Installed cap. (MW)	Max. output (MWh)	Curr. output (MWh)	Cap. factor
S1	2030	17 277	1.51×10^8	1.29×10^8	0.85
S1	2040	65 734	5.74×10^8	3.51×10^8	0.61
S2	2030	22 649	1.98×10^8	1.49×10^8	0.75
S2	2040	75 631	6.61×10^8	4.00×10^8	0.61
S3	2030	16 568	1.45×10^8	1.29×10^8	0.89
S3	2040	63 854	5.58×10^8	3.51×10^8	0.63
S4	2030	22 186	1.94×10^8	1.50×10^8	0.77
S4	2040	74 588	6.52×10^8	4.06×10^8	0.62

In 2040 the capacity factor lies between 0.61 and 0.63 in all four scenarios. This shows that electrolyzers operate as flexible partial-load consumers. The representation changes where and how much electrolyser capacity is built, examined in Section 5.2, but not the fundamental operating mode. This flexible dispatch behaviour is reported in Section 5.6.

In 2030 the capacity factor is higher, between 0.75 and 0.89. The electrolyser fleet is much smaller, electricity is abundant, network capacity is less binding, and there is no unmet demand. The optimiser therefore runs the small 2030 fleet closer to full load. As the fleet grows by 2040 and the system tightens, the electrolyzers spend more time idle and the capacity factor falls. The 2030 factors also differ by scenario, with the two DC-OPF scenarios sitting somewhat lower. DC-OPF builds more capacity in 2030, so the same hydrogen demand spreads over a larger fleet, lowering the factor. The decrease in capacity factor towards 2040 follows the expected shift from a small fleet in an uncongested system to a large fleet in a tightening one.

C.2.2. Price comparison against literature

The corrected nodal prices are compared to Farahmand et al. (2024), which models the same North Sea region over a comparable horizon and extracts prices from dual variables in the same way, as described in Section 3.4. This makes it an appropriate reference for a validity check. The comparison is made for 2040, where the network binds and Farahmand et al. (2024) reports its ranges.

For electricity, the corrected 2040 nodal prices average between 29 and 37 EUR/MWh across the four scenarios. Farahmand et al. (2024) reports baseload prices across the North Sea countries of roughly 20 to 50 EUR/MWh. The model values fall inside this range.

For hydrogen, the corrected 2040 nodal prices average between 41 and 46 EUR/MWh, equivalent to 1.35 to 1.52 EUR/kg using an energy density of 33 kWh/kg. Farahmand et al. (2024) report a levelised

cost of hydrogen of 1.2 to 1.6 EUR/kg, with a base case of 1.4 EUR/kg. The model values fall inside this range.

The two numbers are built differently. Farahmand et al. (2024) do not use a hydrogen dual directly. They treat the electrolyser as an electricity load, take the electricity price from the nodal dual, and add efficiency, the 33 kWh/kg conversion, and capital and operating costs to reach a levelised cost. Electricity is about half of that total. The model used here instead takes the hydrogen price directly from the hydrogen balance dual. The values agree because both are driven by a similar electricity price, which dominates the cost of hydrogen either way.

Both price levels are therefore consistent with an independent model of the same region. Further evidence that the model behaves as expected appears in the dispatch and congestion results in Chapter 5.

D

Exploratory 2050 observations

The main comparison in this study covers 2030 and 2040. This appendix adds 2050 as an exploratory extension, to test whether the onshore-dominant pattern continues beyond the milestone years. It does, and for a different reason than in 2030 and 2040. The 2050 magnitudes, however, are not comparable with the main results, for two reasons set out at the end of this appendix.

The direction is consistent with the main findings. Electrolyser investment remains predominantly onshore in 2050, with an offshore share of only 3% to 5% across the scenarios, lower than in the original runs. The DC-OPF scenarios again show a slightly higher offshore share than the transport scenarios, which follows the same pattern as the original runs.

The reason for the low share is visible in the generation capacity. Offshore hub capacity grows only about 14% from 2040 to 2050, while onshore solar capacity grows about 77% and onshore wind about 34%. Almost all the generation added toward 2050 is therefore onshore, and the offshore hubs stop being the main source of new cheap power. New electrolysis follows the new cheap power onshore, so the offshore share falls. Because this is driven by where generation grows rather than by network congestion, it appears in the transport scenarios as well as the DC-OPF scenarios, which is consistent with the small offshore shares across all four.

In 2030 and 2040 the offshore share is driven by network congestion, which the electricity representation determines. In 2050 it is driven by where new generation is added, which no representation changes. The onshore-dominant result therefore holds under two different mechanisms.

Table D.1: Exploratory 2050 offshore share of electrolyser capacity and dummy activation as a share of electricity demand, per scenario. These values are not comparable with the main 2030 and 2040 results.

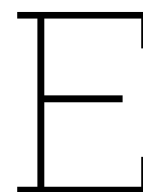
Scenario	Offshore share (%)	Dummy share of demand (%)
S1	4.2	2.68
S2	5.0	2.72
S3	3.1	2.49
S4	4.8	2.53

Two features of the 2050 runs mean their magnitudes cannot be compared with the main results. The first reason is the size of the unmet demand. The model uses dummy producers to keep the problem feasible where real supply cannot meet demand, and the energy they supply measures how much the system falls short. In 2040 this is about 0.2% of electricity demand across the scenarios. In 2050 it rises to between 2.5% and 2.7%, more than ten times larger. A share this size means a meaningful part of the 2050 dispatch, prices, and investment is shaped by where the expensive dummy producers need to be activated rather than by genuine cost-optimal decisions. The shortfall arises because the TYNDP demand projections for 2050 are not matched by the supply and capacity assumptions, leaving a gap the model can only close through dummy activation. The network is not the limiting factor here. As in the main study, the preparatory optimisation was run for the full horizon including 2050, so the fixed

network reflects the transport capacity that is cost-optimal for 2050 supply and demand. The unmet demand in S1 and S3 therefore reflects a shortfall in supply relative to demand, not an undersized grid.

The second reason follows from the multi-year setup. The scenarios optimise all milestone years together with perfect foresight, so investment in each year anticipates the years that follow. Adding 2050 therefore changes the 2030 and 2040 results as well: knowing that a very large and partly unmet demand is coming, the model builds more onshore capacity earlier, and the offshore share in 2040 falls to roughly half of its value in the original runs. The 2050 inconsistency thus propagates back across the whole model horizon. For this reason these runs are kept separate from the main results, and only the 2050 outputs are discussed here.

The 2050 magnitudes are governed by the supply gap and should not be read as quantitative results. A reliable 2050 analysis would require demand and supply assumptions that are consistent with one another, which is left to future work.



Detailed Results

E.1. Energy mix

This section reports the annual dispatched generation by technology, referenced from the operational dispatch cost analysis in Section 5.3. The dispatch cost figure in that section shows the cost of generation, not its volume. The two differ because operational cost per MWh varies widely across technologies: wind, solar, and hydro run at close to zero operational cost, nuclear at around 12 EUR/MWh, and the thermal fleet from roughly 64 EUR/MWh upward. A technology can therefore account for a large share of dispatch cost while supplying a small share of energy, or the reverse. Figure E.1 shows the generation mix for all four scenarios in both milestone years, so it can be read alongside the dispatch cost.

E.2. Nodal prices of all scenarios

Figure E.2 shows the 2040 average nodal electricity prices for all four scenarios. The transport scenarios (S1, S3) and the DC-OPF scenarios (S2, S4) form two clear groups: prices are close to uniform under the transport formulation and widely dispersed under DC-OPF. The two linepacking scenarios are close to each other. This is the price side counterpart of the electrolyser siting result in Section 5.2.

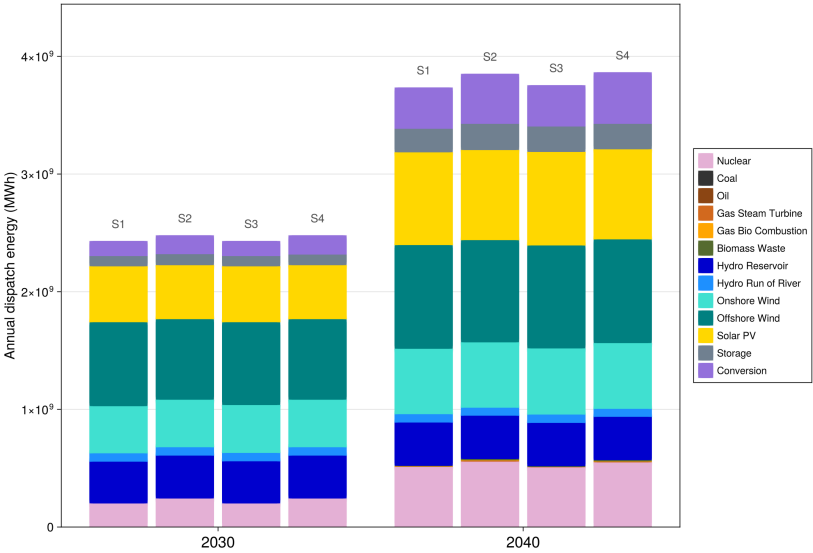


Figure E.1: Annual generation mix by technology, scenario, and milestone year. Shown alongside the dispatch cost in Figure 5.6: the share of energy a technology provides can differ from its share of dispatch cost, because cost per MWh varies widely across technologies.

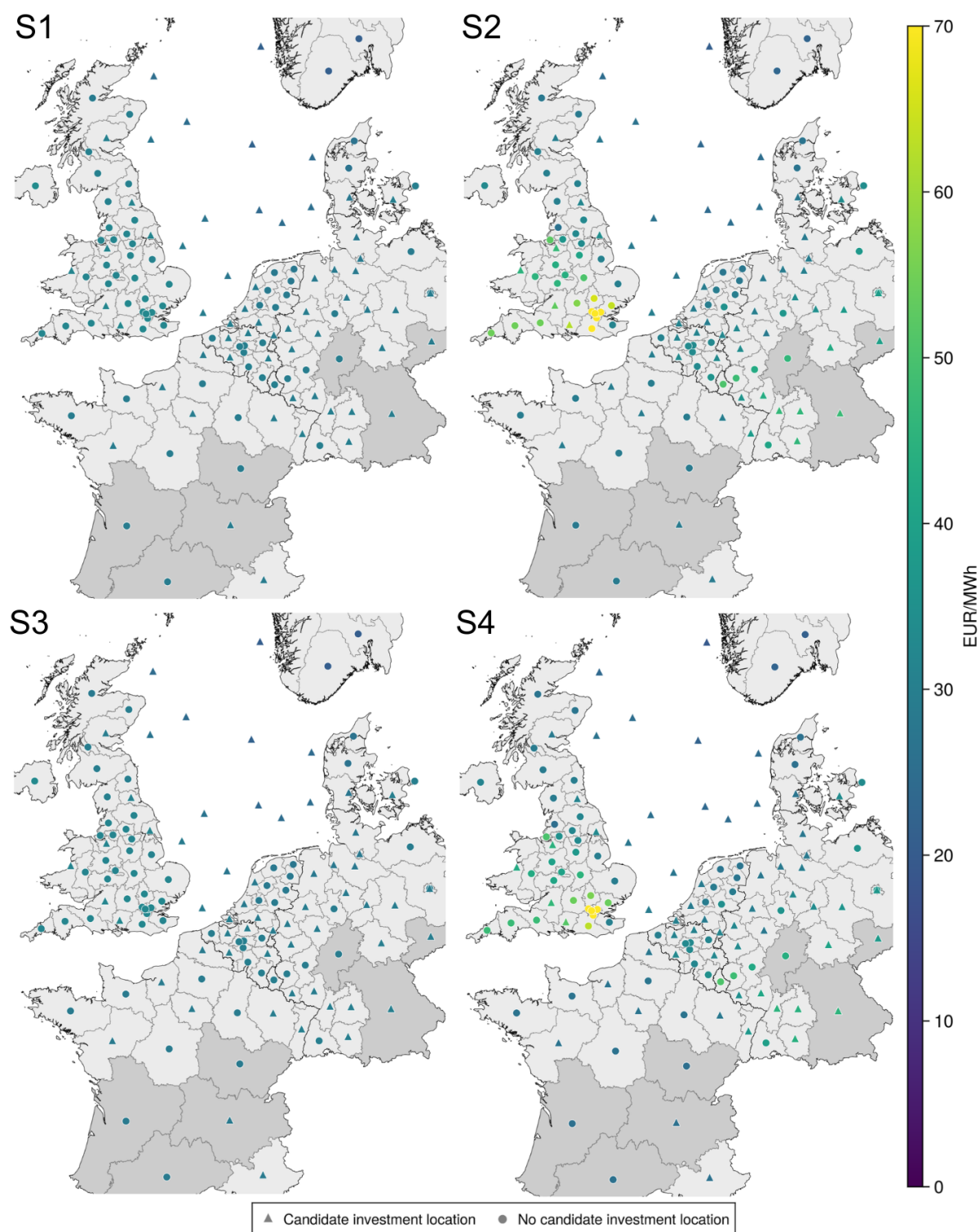


Figure E.2: Average nodal electricity prices in 2040 for all four scenarios. The transport scenarios (S1, S3) show near-uniform prices, with almost every node the same colour (coefficient of variation below 10%). The DC-OPF scenarios (S2, S4) show wide dispersion (40 to 49%). S1 resembles S3 and S2 resembles S4, confirming that the electricity network representation, not linepacking, drives the locational price pattern.