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Hongyu Zhang

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To my loved ones.

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Abstract

This thesis applies operational research methods for the investment planning of energy systems under uncertainty for the energy transition. We develop new models and solution methods.

On the modelling side, we first focus on modelling hydrogen-based offshore energy hubs in an offshore energy system. A mixed-integer linear program is developed for the investment planning of offshore energy systems with offshore energy hubs. The model is then extended to (1) planning under uncertainty using a multi-horizon stochastic programming approach and (2) including the European onshore and offshore energy systems. Finally, some major extensions are made to the model, which lead to the REORIENT model. The REORIENT model is a multi-horizon mixed-integer linear stochastic programming model for integrated investment, retrofit, and abandonment planning of energy systems under short-term and long-term uncertainty. This is the first model that integrates different alternatives and investigates the role of existing energy infrastructure in the energy transition. The REORIENT model features the main modelling contributions in this thesis. In addition, we also extend the modelling of an existing model, EMPIRE, which is a stochastic linear program for the European power system investment planning, by including the modelling of the heat and industry sectors with a strong focus on endogenous decisions regarding decarbonising industry, hydrogen and carbon capture and storage.

Due to the increasing complexity of the models, we contribute to the solution methods. The main idea is to develop algorithms that exploit the special structure of multi-horizon stochastic programming. However, the algorithms developed can also be applied in general multi-stage stochastic programming problems. We develop novel enhanced Benders decomposition and Lagrangean decomposition algorithms. The enhanced Benders decomposition utilises adaptive oracles. In addition, we propose to stabilise the adaptive Benders decomposition with (1) a novel dynamic level method and (2) a novel centre point strategy. We also propose parallelised Lagrangean decomposition with primal reduction. The Lagrangean scenario subproblems are solved in parallel, and the primal problem is reduced based on the special structure of multi-horizon stochastic programming and solved in parallel. We apply the proposed algorithms to solve the REORIENT model and its variations and compare them with standard Benders, unstabilised adaptive Benders, and standard Lagrangean decomposition.

The proposed models and algorithms contribute to operational research and provide useful insights for the energy transition.

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Chapter 1

Introduction

Limiting global warming by 1.5 °C above pre-industrial levels is one of the most important tasks for human beings for the next decades. Decarbonising the energy systems worldwide is important to meet the climate target. The European Union (EU) is a pioneer in the energy transition, and the EU has set an ambitious target to become the first carbon-neutral continent by 2050. Renewable power generation and clean energy carriers are expected to be the pillars of a decarbonised energy system. However, fossil-based energy is still important for many years in the energy transition, especially considering the ever-changing energy reality in Europe. Also, highly valued existing fossil-based energy infrastructures may play an important role in the energy transition. Norway, one of the biggest energy exporters in Europe, has a unique position in the energy transition. On the one hand, it has a mature existing energy infrastructure that transports energy to European countries. On the other hand, it has huge potential for large-scale deployment of clean technologies such as offshore wind, offshore energy hubs and carbon capture and storage. Therefore, in this thesis, we approach the European energy transition problem by first studying the Norwegian offshore energy system and expanding the scope to analyse the European energy system and provide global insights.

The energy transition requires careful planning to be cost efficient, while satisfying physical laws and environmental restrictions. Mathematical programming, a theoretical tool for operational research, minimises or maximises a certain objective subject to some constraints. It has been widely used for energy system planning problems. In addition, dealing with uncertainty has become important in modelling energy system planning problems. For an investment planning problem, long-term and short-term uncertainty can significantly impact investment decisions. Stochastic programming, a part of mathematical programming, deals with optimisation under uncertainty. In this PhD thesis, we apply Multi-Horizon Stochastic Programming (MHSP) and develop corresponding solution methods for energy system investment planning problems.

This line of research and applications forms the basis of this PhD thesis, situated within the broader mission of the LowEmission Research Centre. The centre is dedicated to developing technologies and knowledge to reduce Norwegian offshore emissions, focusing primarily on the emissions from the oil and gas industry. This thesis is written under the PhD program in the Department of Industrial Economics and Technology Management at the Norwegian University of Science and Technology. This PhD project aims to contribute to academic theory and methods and their applications in industry.

In this PhD project, we (1) develop investment planning models for energy systems considering Offshore Energy Hubs (OEHs) and analyse the role of OEHs in the Norwegian offshore energy system and the European energy system, (2) develop an integrated investment, retrofit and abandonment planning model to analyse the role of existing energy infrastructure in the energy transition, (3) include uncertainty in both long-term and short-term time horizons in a long-term planning problem, (4) develop decomposition methods for solving large-scale multi-stage stochastic Linear Programming (LP) and Mixed-Integer Linear Programming (MILP) problems.

The research work of this thesis has led to six papers. The first paper in this thesis considers the investment planning of the Norwegian offshore energy system with OEHs (Zhang et al., 2022c). The second paper extends the work in the first paper by including short-term uncertainty and expanding the system to the European energy system (Zhang et al., 2022b). The problem size increases, and hence the computational burden, which motivates us to develop effective algorithms. The third paper focuses on developing and applying dynamic stabilised adaptive Benders decomposition for investment planning problems (Zhang et al., 2022a). The fourth paper targets a new model REORIENT, and an enhanced Benders decomposition algorithm to solve the model (Zhang et al., 2023a). The fifth paper further investigates the special structure of MHSP, formalises the decomposition algorithms that utilise the structure of MHSP, and develops a parallelised Lagrangean decomposition algorithm (Zhang et al., 2023b). The sixth paper focuses on modelling heat and industry sectors in an investment planning model EMPIRE and analysing the European energy transition without Russian gas (Durakovic et al., 2024).

The structure of this thesis is as follows. Chapter 2 places the papers presented in this thesis into context. It provides background on energy systems planning and the methods used in this thesis, including MHSP, Benders decomposition, stabilisation methods, and Lagrangean decomposition. We provide an overview of relevant literature, place the conducted research in this scientific landscape and elaborate on some of the methods. In Chapter 3, we summarise each paper in this thesis. For each paper, we present the contributions to research and to industry, and specify the individual contributions of each author. Finally, general conclusions based on the research are given in Chapter 4, as well as suggested further work. The papers presenting the actual research are included in the second part of the thesis.

Chapter 2

Background and literature

This chapter places the content of this thesis into the work in the research field and explains how this thesis extends the existing literature. Section 2.1 provides general background and literature on energy system planning. Then additional literature is provided on energy hubs, hydrogen systems, retrofit and abandonment of existing energy infrastructure to highlight our contributions. Section 2.4 presents the relevant research on methodologies, including MHSP, Benders decomposition, stabilisation methods and Lagrangean decomposition.

2.1 Energy system planning

This section gives an overview of operational research in energy system planning. The main methodologies in energy system modelling are divided into top-down and bottom-up categories. Top-down energy models try to depict the economy as a whole on a national or higher level to answer the aggregated effects of energy policies in monetary units. Bottom-up energy system models represent the partial equilibrium or optimisation of a part of the energy sector. In this thesis, we have focused on the bottom-up modelling of energy systems. Typically, energy system planning problems deal with (1) operational optimisation of existing systems, (2) finding optimal investment decisions for a new system or expansion of an existing system, and (3) finding optimal investment decisions and optimal operational decisions according to the investment decisions. Due to the higher penetration of intermittent renewable energies in the energy system and uncertain long-term parameters such as CO_2 price, it becomes essential to manage short-term and long-term uncertainty in energy system planning.

Electric power, natural gas, and thermal systems optimisation have been extensively studied. Sector coupling and multi-carrier energy system optimisations are drawing more attention. The concept of energy hubs is emerging to enable the condition, conversion and storage of multiple energy carriers. In addition to traditional energy carriers, hydrogen can be a pivotal energy carrier in the future, and hydrogen system optimisation is a field of increasing interest. The market assumption of the models for energy system planning is important to understand the results. In the following, we present a brief literature review on the aforementioned topics.

2.1.1 Power system

In this section, we provide a literature review of operational research in power system research. We focus on the literature on capacity expansion, power system scheduling and the penetration of renewable power in power systems. A comprehensive review was presented in Gacitua et al. (2018).

Optimisation models have long been used for power system generation and transmission investment planning. An enormous amount of models have been developed in the past decades. Giving a comprehensive literature review is beyond the scope of the section. However, the models can roughly be categorised based on: (1) spatial representation, (2) temporal representation, (3) network flow modelling, (4) operational details of technologies and (5) uncertainty modelling. In the following, we present some literature on models in these categories and compare the model developed in this thesis with other models.

The spatial resolution of a power system investment planning model can be high or low depending on the specific problems. This is mainly due to the tractability of a model. Skar et al. (2016) studied the European power system capacity expansion under short-term uncertainty and proposed the EMPIRE model. Each EU country was represented by a node in the optimisation model, and Norway was represented by 5 nodes. Many other models used similar spatial resolution (Deane et al., 2017). This may be sufficient for the problem considering such a large-scale system. Antenucci et al. (2019) firstly used the EMPIRE model to obtain the country level investment decisions and then disaggregated the capacity within the country electric buses to provide input to an operational model with higher spatial resolution. Lara et al. (2018) divided the area of scope into regions that have similar climate and load profiles. In addition, the generators and storage units with similar characterises were aggregated in each region. Using this, the Texas region, ERCOT, was represented by five nodes in an optimisation model. However, the length limit of an electricity transmission line was not considered in the spatial aggregation. In our paper (Zhang et al., 2022c), we use a k-means cluster approach that considers the transmission line limit. It is important because, in each aggregated region, it should be feasible to transmit electricity. We also adopt the approach in Skar et al. (2016) and Lara et al. (2018) for regions that require less resolution. In this way, we achieve a better balance between spatial resolution and computational tractability.

Temporal representation includes the representations of two time horizons: the investment time horizon and the operational time horizon. In the investment time horizon, there are one-time investments and multi-period investments. The one-time investment problem is also referred to as a greenfield problem. For the investment time horizon with multiple periods, a yearly resolution was used meaning that the investment decisions are made yearly in a model. Models such as COMPETES (Ozdemir et al., 2016), DSIM (Strbac et al., 2012) and the model in Li & Grossmann (2019) have a yearly resolution. However, a lower resolution was used to make the model tractable (Skar et al., 2016). In this thesis, we use a 5-yearly investment resolution to reduce the model size.

The temporal representation of the operational time horizon is important because it can directly affect the feasibility of investment decisions. If the operational time horizon is poorly modelled, the investment decisions from the model can be infeasible or cannot deliver enough power in the real world. Normally, the operational resolution for an investment planning model is hourly (Munoz et al., 2014) or even multi-hourly (Jaehnert et al., 2013) to reduce the problem size. In addition, the model is usually run on some selected time slices instead of every time period in a whole year such as in Backe et al. (2022a). This is a compromise to keep the model tractable. However, there is a risk of missing some operational conditions in some operational periods. It is very difficult to include a whole year of system operation and still be able to solve the model. To the best of our knowledge, there is no literature on solving a long-term multi-step power system investment planning problem with an annual system operation with an hourly operational time resolution. In this thesis, we close the research gap by developing models with a whole year half-hourly operational time resolution and proposing novel decomposition algorithms to solve huge-scale models very efficiently (Zhang et al., 2022a).

The modelling of electricity networks can be divided into Alternating Current (AC) power flow, Direct Current (DC) power flow and transport approaches. AC optimal power flow takes both real and reactive power, and phase angles between them into consideration. This keeps all the physics but leads to nonlinear optimisation models. Due to the computational difficulty, much fewer studies have used AC power flow in investment planning problems than the other two approaches. Krishnan et al. (2016) formulated an AC power flow capacity expansion model but could not solve it. Alguacil et al. (2003) proposed a mixed-integer linear formulation to approximate the original nonlinear nonconvex problem. As can be seen, it is very challenging to solve an AC power flow model. DC power flow ignores reactive power and phase angles and focuses on the real power. This simplification can be used at the expense of approximating the physics of the electricity transmission, but with the great advantage that it leads to a linear formulation. It has been used in Li et al. (2022); Chaudry et al. (2008); Zlotnik et al. (2017). The transport model for electricity network expansion is a more common approach in the literature, including the EMPIRE model (Backe et al., 2022a), COMPETES (Ozdemir et al., 2016) and DSIM (Strbac et al., 2012). In this thesis, improving the modelling of the electricity network is not the focus. Therefore, we adopt the transport modelling approach.

Managing uncertainty in a capacity expansion problem is necessary for modern power system investment planning. It is because: (1) operational condition is highly uncertain with the increasing penetration of intermittent renewable power, and (2) long-term uncertainty such as policy, and power demand have a significant impact on the investment decisions. Stochastic optimisation models can capture uncertainty in key parameters that may significantly affect investment decisions. Munoz et al. (2016) modelled a multi-area transmission and generation planning in an MILP model and extended the model to stochastic programming by using expected-value constraints to enforce policy objectives. In Singh et al. (2009), a multi-stage stochastic MILP model was proposed for capacity planning problems, and a case study was demonstrated for the New Zealand electricity distribution network expansion under demand uncertainty. MILP has been widely used for investment planning problems because integer or binary variables are needed to capture the economic scale. However, one challenge in MILP models is their computational difficulty, especially when the model is stochastic. Managing uncertainty is relevant to the power system expansion problem and the capacity expansion problem in general. Therefore, we will provide a more systematic literature review in Section 2.1.7.

In power system operational optimisation problems, many challenges are similar to those in investment planning problems. For example, in power system operational optimisation, the unit commitment problem is fundamental (Anjos & Conejo, 2017). It is designed to find the cost-optimal scheduling of each generating unit to meet the electricity demand. Unit commitment has been used for hydro-thermal generation scheduling since the generators are controllable. Unit commitment has been used to model the power system part of several energy system models such as IMAKUS model (Heilek et al., 2015), Dispa-SET model (Kavvadias et al., 2018), Oemof model (Hilpert et al., 2018), and the model developed in Li et al. (2008). Unit commitment problems can be modelled as mixed-integer optimisation problems. However, as volatile renewables have a higher penetration in the system, stochastic optimisation models for unit commitment have drawn increased interest. Schulze et al. (2017) developed a stabilised scenario decomposition algorithm with novel primal and dual initialisation techniques to solve two-stage and multi-stage unit commitment models. Hydro-electric unit commitment subject to uncertain demand was studied in Philpott et al. (2000), and the inflow uncertainty in hydropower unit commitment was studied in Séguin et al. (2017). Modelling the physics of an electricity network in an operational problem is more important than that in an investment planning problem. AC power flow is more commonly used in operational optimisation problems. However, solving the AC power flow problem is still challenging. Therefore, solution methods for the AC power flow problem have been an active research area. AC power flow was used to represent the electricity network, and the equations were linearised and solved using Newton's method (Martinez-Mares & Fuerte-Esquivel, 2012). A piecewise linear approximation of AC power flow was developed (Trodden et al., 2014). Spatial and temporal hierarchical decomposition methods for optimal power flow problems were developed (Nava, 2022).

2.1.2 Natural gas system

The infrastructure design of natural gas systems is crucial. Two important parts of developing a natural gas system are the development of fields and the design of the transmission system.

Norway was the third largest natural gas exporter and has the largest offshore pipeline network in the world. This motivated much research in the investment and operational optimisation of the Norwegian natural gas system. Due to Norway's significant role in the natural gas industry, the research has provided global insights.

A deterministic MILP was developed for natural gas infrastructure analysis for the Norwegian continental shelf (Hellemo et al., 2012). The model handled strategic decisions including developing new fields, and constructing and redesigning the infrastructure with operational details such as the relationship between pressure and flow and gas quality. The model was deterministic but was extended to a multi-stage stochastic optimisation model, Ramona. The Ramona model has then been used for the stochastic analysis of the investment planning of the Norwegian continental shelf (Hellemo et al., 2013). Hellemo et al. (2013) combined short-term and long-term uncertainty in the case studies, but did not sufficiently address the computational solution for solving the model. This has remained as a research gap for more than ten years, and we bridge the gap by proposing novel decomposition algorithms to solve large-scale investment planning problems with short-term and long-term uncertainty (Zhang et al., 2022a, 2023a). The Ramona model was then used to analyse European infrastructure development under demand uncertainty (Fodstad et al., 2016). However, the uncertain parameters were only revealed at one stage, making it only a two-stage stochastic program. It is a computational challenge to solve multi-stage stochastic programming, and two-stage stochastic programming is a compromise. The algorithms we develop in this thesis overcome the challenge and enable more research in infrastructure planning including short-term and long-term uncertainty.

There are more research gaps in the infrastructure planning of natural gas systems. For example, the existing literature (Hellemo et al., 2013; Fodstad et al., 2016) did not consider retrofit and abandonment planning of existing infrastructures in their models. The potential value of existing oil and gas infrastructures for the energy transition has been missing in the literature. Therefore, we bridge the gap by considering retrofit and abandonment planning of existing energy infrastructures in an investment planning model (Zhang et al., 2023a).

Modelling the planning of oil and gas field infrastructure is a complex task. The modelling can be simplified such as in Fodstad et al. (2016), but it can also be dealt with so that more physical laws are respected. Tarhan et al. (2009) proposed a nonconvex mixed-integer nonlinear programming model to solve an offshore oil and gas field infrastructure planning problem under decision-dependent uncertainty. The modelling of the reservoir led to nonlinearity. Goel & Grossmann (2004) proposed a multi-stage stochastic MILP for offshore gas field developments under reserve uncertainty. Although they considered decision-dependent uncertainty, short-term uncertainty was not considered. From a methodology perspective, the advanced models and algorithms developed for oil and gas field infrastructure planning are valuable, but developing more oil and gas fields may slow down decarbonisation. Therefore, in this PhD thesis, we do not consider developing new oil and gas fields, but rather focus on decarbonising existing oil and gas fields (Zhang et al., 2022c) and retrofitting oil and gas infrastructures for the energy transition (Zhang et al., 2023a).

One challenge of modelling natural gas systems is modelling the physics of the gas flow and pressure. It is because of the nonlinear properties in pressure dynamics in pipelines, compressor efficiency and gas quality management. Li et al. (2017) proposed two two-stage stochastic nonconvex mixed-integer nonlinear programming models for the production network infrastructure development under uncertainty and proposed nonconvex generalised Benders decomposition to solve the model. Qadrdan et al. (2014) took the nonlinear characteristics of the gas network into consideration and proposed solving the problem using successive linear programming. There are several approximation methods to avoid nonlinearity. Fodstad et al. (2015) used a linear steady approximation of the pressure dynamics in pipelines, which was claimed to be a reasonable approximation. In this thesis, we use an energy flow model to model gas transport considering the large scale of the system (Zhang et al., 2023a).

2.1.3 Thermal system

Thermal system optimisation has not been researched as much as power and natural gas systems optimisation.

Thermal system has the potential to aid energy system decarbonisation using demand side management. For example, Egging-Bratseth et al. (2021) developed a stochastic programming model to minimise the operational cost of a district heating network with local waste heat utilisation, seasonal storage and uncertain demand. They investigated demand side management and seasonal storage for improving operational flexibility. The model did not include many physical details such as heat mass and temperature change with respect to energy consumption, but the simplification was sufficient for a large-scale system. Salerno et al. (2021) investigated building level energy management. Heat management was a major part of their model, and due to the relatively small spatial scale, they managed to include more physical details such as room temperature change energy exchange, leading to a nonlinear optimisation model.

Existing literature is mainly centred around domestic heating systems. Staffell et al. (2012) provided a comprehensive of domestic heat pumps and pointed out that heat pump is a promising technology that can radically improve the heating sector around the world. Backe et al. (2022b) combined two models, EMPIRE and GUSTO to investigate the impact of energy communities on the European electricity and heating system. They found that heat pumps may supply 50% of European heat demand by 2025. Due to the model size, the physics of the heating system was simplified to a large extent. Felten (2020), on the other hand, managed to include more detailed modelling of the district heating network in Europe. From the literature, we can see that offshore heating system optimisation is missing. Compared with domestic heating, the offshore heating system is smaller but also important. Offshore heating is important for oil and gas production and the living facilities on the oil and gas platforms. The offshore heat energy is largely provided by heat recovery from gas turbines. However, once the gas turbines are replaced by renewable power generation, the heat supply must also be provided by other means. To fill this research gap, we propose an MILP model for the offshore energy system considering offshore heating system (Zhang et al., 2022c).

2.1.4 Hydrogen system

Compared with well-studied systems like power and natural gas systems, the hydrogen system has the potential to be the pillar of the future decarbonised energy system and is drawing increasing interest in academia and industry. There is a high expected demand for hydrogen by 2050 in Europe and the UK (van Rossum et al., 2022). Much literature has appeared on the operational and investment planning optimisation of hydrogen systems.

Hydrogen infrastructure planning is the main focus of the literature. Bødal et al. (2020) developed an investment planning model for hydrogen infrastructure design and found that in Texas by 2050, hydrogen produced from electricity and natural gas will be cost-effective for emissions reduction. The model was a single step investment model assuming the costs of technologies in 2050. This means the model cannot provide insights for the hydrogen infrastructure pathway. In this thesis, we develop a multi-step investment planning model. Reuß et al. (2019) used a single step investment model to study the hydrogen supply chain with spatial resolution. Different infrastructure options nationwide in the German energy system in 2050 were assessed, showing that salt caverns and transmission pipelines are key components in future infrastructure systems. The limitation of their study is that the authors only investigated the system under the 2050 assumption, which is highly uncertain. Managing uncertainty in hydrogen infrastructure planning is very important because hydrogen demand is significantly more uncertain compared with traditional energy carriers such as electricity. In this thesis, we conduct hydrogen infrastructure planning considering operational and investment uncertainty (Zhang et al., 2023a).

One common limitation of existing literature regarding hydrogen infrastructure planning is that hydrogen demand is usually an exogenous parameter. For example, Durakovic et al. (2023b) investigated the impact of hydrogen investments on power grid infrastructure and power prices. They considered major offshore wind projects in the North Sea and conducted European wide analysis. The hydrogen demand in the model was given as a parameter. Although the transport of hydrogen was considered in their model, the analysis of long-term hydrogen pipeline development was missing. Seo et al. (2020) studied the hydrogen infrastructure for fuel cell electric vehicles focusing on the storage and transport of hydrogen using different means. The authors investigated using centralised hydrogen storage to supply hydrogen at fuel stations. The transition to hydrogen is promising based on van Rossum et al. (2022) but is less clear due to the ever changing energy reality in Europe. Therefore, using exogenous hydrogen demand for hydrogen infrastructure design can be misleading. The ideal way to plan hydrogen infrastructure is to endogenously model the hydrogen demand (Seck et al., 2022; Pedersen et al., 2022), which has not been sufficiently studied in the literature. In this thesis, we bridge this gap by (1) modelling the endogenous hydrogen demand in the offshore oil and gas industry and planning the hydrogen production infrastructure on the Norwegian continental shelf (Zhang et al., 2022c,b), and (2) modelling the transition to hydrogen in the industry, heat, and transport sectors and analysing European decarbonisation without Russian gas (Durakovic et al., 2024).

Optimising hydrogen production is another focus in the literature. Hydrogen can be produced from water electrolysis, steam reforming of natural gas and others. Based on the production methods and their emissions, hydrogen is often categorised into different colours. The energy optimisation of hydrogen production from biomass was studied using an MILP model (Martín & Grossmann, 2011). The authors found that indirect gasification with steam reforming is the preferred technology providing higher production yields than natural gas steam reforming. The authors mainly focused on the hydrogen production method and did not analyse how the proposed approach can benefit the energy transition. Using an energy hub to produce hydrogen was investigated in Lüth et al. (2023). The authors investigated the optimal way of connecting energy hubs with surrounding countries considering cables and pipelines. They only considered the onshore demand for hydrogen but omitted the potential hydrogen consumption in the offshore energy system. This thesis considers both onshore and offshore hydrogen demand and production (Zhang et al., 2022c, 2023a).

Carbon capture and storage is an important technology in hydrogen systems due to the potential importance of blue hydrogen in the future energy system. Cloete et al. (2022) investigated the potential trade channels for energy exporters in a low-carbon future using a novel electricity-hydrogen-steel energy system model. The analysis showed that a robust hydrogen demand would allow Norway to export all natural gas production as blue hydrogen profitably. Moreno-Benito et al. (2017) used an extension of the SHIPMod model to optimise the hydrogen supply chain and carbon capture and storage systems simultaneously. The results showed that the most cost-effective hydrogen production method that maintains low carbon emissions is natural gas reforming with carbon capture storage (Moreno-Benito et al., 2017). Their model was a multi-period spatial-explicit model but did not consider uncertainty. In this thesis, we consider carbon capture and storage system design alongside hydrogen infrastructure design with endogenous hydrogen demand under short-term uncertainty (Durakovic et al., 2024).

2.1.5 Multi-carrier energy system

From Sections 2.1.1-2.1.4, we can see that: (1) power, natural gas and thermal systems optimisation has been extensively studied in the past decades, and (2) hydrogen system optimisation is drawing more attention as hydrogen may be a pivotal energy carrier in the future energy system.

Another important aspect of energy system planning is multi-carrier energy system planning. It becomes important because managing better the interaction among power, heat, natural gas and hydrogen systems can potentially lead to a more reliable, clean, and cost effective energy system. In this thesis, we integrate power, natural gas, heat and hydrogen systems in a single multi-carrier energy system model (Zhang et al., 2022c, 2023a; Durakovic et al., 2024). The following presents the literature review on sector coupling. A comprehensive review on the state of the art of energy system modelling including multi-energy systems was presented in Fodstad et al. (2022).

Power and gas systems can be coupled by gas-fired power plants. A thorough survey on the state of the art of the integrated power and natural gas networks models was conducted in Farrokhifar et al. (2020). The difficulty of power and gas system coupling is the complexity of both systems. As mentioned in Sections 2.1.1 and 2.1.2, there are complex equations to capture the physics in both systems. Even solving a problem with one sector is computationally difficult. Therefore, coupling the systems in a tractable way and developing solution methods are important. Qadrdan et al. (2014) integrated GB gas and electricity system by having separated electricity model and gas model, and using gas load shedding due to the gas demand for electricity generation as the coupling factor. The strength of this approach is that more physics can be included in the two separate models. However, the solution is not global optimal. Unlike Qadrdan et al. (2014), Chaudry et al. (2008) proposed to solve an integrated gas and electricity network investment planning as a single nonlinear programming problem, and a DC network was used to represent the electricity network. To aid the convergence, a feasible starting point was provided, and the decision variables were scaled. Due to the complexity of the models, they only considered single step investment planning. Nunes et al. (2018) managed to include uncertainty in an integrated electricity and gas system and conducted multi-step investment planning. However, they only considered the uncertainty at the operational level and made more simplifications on the modelling of the network to reduce the complexity. From the literature, we can identify that a research gap is the lack of a combination of high operational modelling detail, high investment time resolution and managing uncertainty properly. This thesis contributes to this issue by proposing a tractable multi-carrier energy system model with multi-step investments and short-term and long-term uncertainty, and the solution method (Zhang et al., 2023a).

Although directly coupling gas and electricity systems in a model faces computational difficulty, there may be more issues with this approach in real life. The gas and electricity systems are operated by different entities, and it is unlikely that a single operator operates both systems. Therefore, there are also studies to couple gas and electricity using price signals. For example, Chen et al. (2020) investigated the independent, but interrelated day-ahead operation of power and natural gas systems with information interchange on prices, operational costs and decisions. Their results showed that the coupling approach introduced overall efficiency losses and increased the operational cost of the gas system. We can see that there is still more work to find an integration mechanism that can be used in real life.

In addition to gas and electricity system coupling, heat and electricity systems are coupled by combined heat and power generators, electric boilers, and heat storage. The heat and electricity coupling enables to deliver heat alongside electricity. Felten (2020) coupled the heat and power sectors using a sequential approach. The heat demand was firstly modelled at the district heat network level, then the heat supply was determined, and finally the electricity market was simulated. Although a European wide heat and electricity system was considered, the system was only simulated not optimised. Backe et al. (2021) extended an optimisation based model EMPIRE to include the heat sector in a power system investment planning model. The authors found that the non-electric heat supply in Norway is attractive for Europe towards 2060. The German electricity and heat sector coupling was modelled in Henning & Palzer (2013), and Palzer & Henning (2014) found that it is feasible for a 100% renewable supply. To the best of our knowledge, the integrated heat and electricity system for offshore energy systems is missing in the literature. In the offshore energy system, especially the offshore oil and gas industry, heat and electricity are important energy carriers for production activities. Decarbonising the heat and electricity supply for offshore energy systems is a research gap. In this thesis, we bridge this gap by proposing a multi-carrier energy model to decarbonise the offshore oil and gas sector (Zhang et al., 2022c).

Hydrogen, natural gas and power systems are closely related to each other. Green hydrogen can be produced from electrolysis using clean electricity such as wind power, solar power and hydropower. Bødal et al. (2020) developed a coupled hydrogen and electricity investment planning model to investigate the decarbonisation synergies from joint planning of electricity and hydrogen production. They modelled the electricity and hydrogen network using a transport model to reduce the complexity. The model was a single step investment model. This may be sufficient for analysing the costs of production but not enough for analysing the role of hydrogen in the decarbonisation pathway of the energy system. Therefore, in this thesis, we close the gap by proposing a coupled hydrogen and electricity system multi-step investment planning model (Zhang et al., 2023a; Durakovic et al., 2024). The value of flexibility of hydropower for hydrogen production was investigated in an operational optimisation problem, which allowed the inclusion of more modelling of the technical details (Bødal & Korpås, 2020). Blue hydrogen can be produced from natural gas with carbon capture and storage, which motivates the sector coupling of hydrogen and natural gas systems. Although there is no large-scale hydrogen system in real life, academic literature has started investigating the co-optimisation of natural gas and hydrogen systems. For example, Sunny et al. (2020) developed an optimisation model that determines the optimal hydrogen and CO_2 infrastructure for investigating the decarbonisation of a heat system that connects to an existing natural gas network. The literature either focused only on either the planning of hydrogen and electricity systems, or the planning of hydrogen and natural gas systems. Therefore, in this thesis, we integrate power, natural gas, heat and hydrogen sectors in a single model to better analyse the interactions. Furthermore, the uncertainty is not managed sufficiently in the literature (Fodstad et al., 2022). In this thesis, we extend the literature by proposing an MHSP model for integrated energy system planning with short-term and long-term uncertainty.

2.1.6 Market assumptions in energy system infrastructure planning

Understanding the market assumptions of an energy system planning model is crucial for analysing the results. In this thesis, the models developed take a social planner standpoint. Most of the energy system infrastructure planning models took the same assumption. For example, EMPIRE (Backe et al., 2022a) and PRIMES (E3MLab/ICCS, 2018) models considered long-term European energy system planning from a social planner perspective. This means that the decisions made are the most cost effective for society but are not necessarily what firms would actually make in a real market. Although there are studies assuming a more realistic market, such as Linares et al. (2008) which incorporated oligopoly in a power generation expansion model, such models are hard to solve due to the complementarity. In this thesis, we are interested in studying the optimal investment planning of the large-scale European energy system, a social planner based model reduces the computational difficulties.

2.1.7 Managing uncertainty in energy system planning

Managing uncertainty is an important task in energy system planning. Yue et al. (2018) conducted a comprehensive review on managing uncertainty in energy system optimisation models. The authors pointed out four classes of methods to address uncertainty, including Monte Carlo analysis, stochastic programming, robust optimisation and modelling to generate alternatives. Stochastic programming is the most widely used method to tackle uncertainty in energy system models, which is also the method used in this thesis. In the following, we present a literature review on stochastic programming in energy system investment planning.

Long-term energy system investment planning faces uncertainty in operational time horizon and investment time horizon. Operational uncertainty and investment uncertainty can have a decisive impact on investment decisions. From a modelling perspective, including both types of uncertainty simply leads to multi-stage stochastic programs.

Using traditional multi-stage stochastic programming to manage investment and operational uncertainty for long-term energy system investment planning problems is inefficient. Singh et al. (2009) developed a multi-stage stochastic programming model for electricity network capacity expansion considering only long-term uncertainty in future demand growth. Lara et al. (2020) included operational and investment uncertainty in a long-term power system expansion planning problem. They considered long-term uncertainty in fuel prices and CO_2 tax, and short-term uncertainty in renewable power production and hourly demand. The problem grew exponentially because the scenario tree was branched based on both investment and operational uncertainty. Liu et al. (2017) developed a similar multi-stage stochastic programming model to capture long-term fuel, and demand growth uncertainty and renewable availability uncertainty. Although, Lara et al. (2020) and Liu et al. (2017) are two of the few papers that managed to consider uncertainty from both time horizons, their models based on traditional multi-stage stochastic programming have a limitation which is the explosion in the size of the scenario tree. Their models can very easily become intractable. The state-of-the-art modelling approach for including uncertainty in the operational and investment time horizons is MHSP. MHSP has been widely used in energy system investment planning since it was first proposed in Kaut et al. (2014). In this thesis, we also use MHSP in the energy system investment planning model. We provide a systematic review of the methodology of MHSP in Section 2.4.1.

Although MHSP has been widely used for energy system investment planning models, there are two limitations in the existing literature: (1) only operational uncertainty has been considered, and (2) the operational uncertainty is only represented by a few representative days. Durakovic et al. (2023b) included operational uncertainty including wind and solar capacity factors, and hydropower production profile in a multi-step energy investment planning model using the MHSP approach. Backe et al. (2021) used an MHSP model to investigate the sector coupling between a central power system and energy communities under short-term uncertainty. The operational uncertainty was represented by representative time slices, which led to a two-stage stochastic programming model and was arguably sufficient for an investment planning problem. However, there is a risk of missing some critical operational conditions from the rest time periods. In addition, only considering operational uncertainty loses the value of MHSP which is managing both operational and investment uncertainty more efficiently than traditional multi-stage stochastic programming. To the best of our knowledge, there was no paper that included operational and investment uncertainty using MHSP for an energy system planning problem since MHSP was proposed. In this thesis, we close the research gap by developing the first multi-carrier energy system investment planning model considering operational and investment uncertainty (Zhang et al., 2022a). Furthermore, we are able to include an annual operational problem with half-hourly time periods compared with representative time slices in the existing literature (Zhang et al., 2022a).

The growing complexity of energy system models motivates the development and application of decomposition methods. This is especially the case for stochastic energy system planning problems because stochastic programming models have structures that can be easily decomposed. For example, nested Benders decomposition with Lagrangean relaxation (Lara et al., 2018), Benders decomposition with a two-phase bounding scheme (Munoz et al., 2016), and Dantzig-Wolfe decomposition (Singh et al., 2009) have been proposed to solve their problems.

In this thesis, we develop enhanced Benders decomposition and parallel Lagrangean decomposition methods that utilise the special structure of MHSP. The enhanced Benders decomposition allows us to solve by far the largest problems instances in energy system planning literature (Zhang et al., 2022a). We provide a more detailed literature review on Benders decomposition and Lagrangean decomposition presented in Sections 2.4.2 and 2.4.4.

2.2 Energy hubs

In this thesis, we propose the concept of OEHs for the energy transition. In the following, the relevant literature regarding energy hubs is provided.

2.2.1 The energy hub concept

The energy hub concept, originally introduced by Geidl et al. (2007), is described as a physical junction where various types of energy can be transformed, conditioned, and stored.

The energy hub concept has drawn much research interest due to its multi-carrier nature. For example, the concept has been utilised to enhance energy flexibility in buildings (Ottesen & Tomasgard, 2015) and electricity markets (Ottesen et al., 2016). Energy hubs provide a promising means for tapping into the advantages of multi-energy systems, such as interconnected electricity and heating networks (Ayele et al., 2018), and electricity-thermal-natural gas coupling systems (Wang et al., 2019). Moreover, the management of energy hubs with intermittent wind power has been investigated using stochastic programming (Najafi et al., 2016). Employing energy hubs to tackle the volatility of wind power can reduce operating costs, wind power reduction, and CO_2 emissions (Zare Oskouei et al., 2021). Energy hubs with power-to-gas and hydrogen storage technologies can curtail emissions and generate hydrogen for end-use applications (Preston et al., 2020). A comprehensive review on energy hubs was conducted in Mohammadi et al. (2017).

2.2.2 Offshore energy hubs

Although the energy hub concept was widely studied, OEHs are less researched. OEHs essentially apply the concept of energy hubs for offshore energy systems.

In the context of offshore energy systems, the definition of energy hubs is generalised. For example, North Sea Wind Power Hub Programme (2020) proposed a North Sea wind power hub to connect the North Sea countries using OEHs in a hub and spoke form. Danish Energy Agency (2020) aims to construct the first energy island in the world. The energy island is essentially a wind power distribution hub. The conversion and storage functions of the energy hub concept are not strictly considered in the definition of OEHs. Durakovic et al. (2023a) modelled green hydrogen production via OEHs to supply the European energy system and they only considered energy conversion and condition in OEHs. Lüth et al. (2023) compared connecting the offshore energy island to the surrounding countries via electricity cables and hydrogen pipelines. The energy island is an electricity conversion and transmission hub if it connects with the onshore system via cables. In the literature, the storage function of OEHs has not been considered. To bridge this gap, we first propose clean OEHs with storage function and show that hydrogen storage is important to balance offshore renewables intermittency for a near zero offshore energy system (Zhang et al., 2022c).

The potential value and functionality of OEHs have drawn interest in various sectors. In the offshore oil and gas sector, it was discovered that the energy hubs used to import energy from multiple sources to offshore oil and gas platforms could dramatically reduce CO_2 emissions in the UK continental shelf (Elgenedy et al., 2021). It was highlighted that hydrogen storage is environmentally friendly and ensures a stable supply for oil and gas operations. An energy-hub-based electricity system design, with CO_2 mitigation taken into consideration for offshore platforms, was presented in Zhang et al. (2017). The proposed approach on an existing platform determined that a CO_2 tax could significantly impact emission mitigation for offshore platforms. In addition to clean OEHs that harness offshore wind, an OEH equipped with large gas turbines was proposed in Flórez-Orrego et al. (2021). Such an OEH is a centralised power generation system that delivers higher efficiencies than platform-located gas turbines (Flórez-Orrego et al., 2021). A limitation of existing literature is that the impact of OEHs on larger offshore energy systems decarbonisation is not properly analysed. To extend the literature, we develop a series of models to analyse the value of OEHs in the Norwegian offshore energy system (Zhang et al., 2022c), and in the European energy system (Zhang et al., 2022c,b).

In addition to system design with OEHs, studies have also been conducted on the impact of markets and the market design of a system with OEHs. The impact of the North Sea energy islands on national markets and grids was analysed in Tosatto et al. (2022) using European electricity market and network models. The authors found that social welfare increases, but not for all the countries when the North Sea energy hub is included in the system. Kitzing & Garzón González (2020) found that a separate offshore bidding zone may lead to a more efficient offshore energy system with OEHs. As a novel concept, OEHs need to be more researched both in a new market design and an optimal infrastructure design to better harness offshore renewable energies for the overall energy transition. In this thesis, we focus on the infrastructure design of energy systems with OEHs (Zhang et al., 2022c,b, 2023a).

2.3 Existing energy infrastructure

Existing energy infrastructure can play an important role in the energy transition. For example, the existing oil and gas production sites can potentially be retrofitted to produce green hydrogen, and the existing gas pipelines can be potentially used for hydrogen distribution. Otherwise, existing infrastructure is likely to be abandoned at a high cost. The economic trade off between new investment, retrofit and abandonment should be properly investigated. In the following, we provide a brief literature review on retrofitting and abandonment planning of existing energy infrastructure.

2.3.1 Retrofitting existing energy infrastructure

Retrofitting existing energy infrastructure could prove beneficial for the energy transition. In grassroots design, process decisions are followed by equipment decisions, but the retrofit design also demands models capable of rating existing equipment for proper analysis.

A comparison between grassroots and retrofit design has been discussed in Grossmann et al. (1987). The combinatorial nature of retrofit planning problems adds to the complexity of these models. The reasons for retrofitting are numerous, including (1) the processing of a new feedstock, (2) improving economics by using less energy per unit of production, (3) creating a new product, and (4) increasing the conversion of the feedstocks, among many others. This paper considers retrofitting for the creation of a new product. A strategy for debottlenecking was suggested for the retrofit problem (Harsh et al., 1989). A systematic procedure for retrofitting heat exchanger networks was presented in Yee & Grossmann (1991). The retrofitting of heat exchangers has been extensively studied over the past decades (Pan et al., 2013; Wang et al., 2012). The retrofit approach was divided into a prescreening stage and an optimisation stage. The prescreening step determined the economic feasibility of the retrofit project, and then the best retrofit was determined in the optimisation stage. A high-level optimisation model for the retrofit planning of process networks was presented in Jackson & Grossmann (2002), which addressed retrofitting over several time periods. The proposed strategy included a high-level analysis of the entire network and a low-level analysis of a specific process flowsheet. The problem was formulated using a multi-period generalised disjunctive programming model, which was reformulated as an MILP model via the convex hull formulation.

Given the growing demand for hydrogen, retrofitting existing oil and gas infrastructure for hydrogen production and transportation is gaining more attention. Most offshore pipelines can be utilised for hydrogen transport in Europe (Cauchois et al., 2021). The European hydrogen infrastructure could evolve into a pan-European network by 2040, primarily based on repurposed existing natural gas infrastructure (van Rossum et al., 2022). In contrast, only a minor portion of the onshore pipelines would be reusable for CO_2 transport. Retrofitting the existing offshore platform for green hydrogen production is underway (Neptune Energy, 2023).

It is observed that retrofitting might become a key component during the energy transition. Hence, the traditional capacity expansion model alone might not suffice to plan investments at minimum cost. In addition, the existing literature was mainly from a process design perspective, not an energy system planning perspective. Therefore, in this PhD thesis, the existing literature has been extended by developing the concept of retrofitting the existing energy infrastructure for green hydrogen production and distribution in an energy system planning problem (Zhang et al., 2023a).

2.3.2 Abandonment of existing energy infrastructure

The evaluation of the worth of the current energy infrastructure, particularly oil and gas infrastructure, is crucial in addition to planning investments for the power system and future hydrogen system. The oil and gas industry entails investments and profits in the billions of dollars. The existing energy infrastructure could greatly aid the energy transition. Abandoning the existing infrastructure would incur considerable costs (Bakker et al., 2019). The costs of plugging and abandoning are estimated to be between £5-15 million per well for the upcoming decade, with thousands of wells set to be abandoned, particularly in offshore regions.

Abandonment campaign modelling is complex and models have been developed only for abandonment planning. Bakker et al. (2019) modelled the plug and abandonment campaign as an uncapacitated vehicle routing problem with time windows. The model was an MILP that minimises the cost of plug and abandonment for a number of subsea wells. The authors focused on the detailed plug and abandonment for each well. In this thesis, we aggregate the wells in each oil and gas field to reduce the size of the problem. It is sufficient for a model that integrates investment, retrofit and abandonment planning due to its complexity.

Optimisation models for only the plug and abandonment campaign can be hard to solve. Bakker et al. (2021) developed a real options model for optimising the development of mature fields, including the options of shut down, and plug and abandonment. The problem grew large after including uncertainty because it became a multi-stage stochastic MILP. The authors applied stochastic dual dynamic integer programming, originally proposed by Zou et al. (2019) to solve this complex real options model. The author also briefly discussed the difference between real options and stochastic programming. In this thesis, we use stochastic programming to manage uncertainty.

Abandonment planning is not the main focus of the thesis, and we refer the readers to Vrålstad et al. (2019) for an overview of plug and abandonment operations. A common limitation of existing literature is that only abandonment planning is considered in the models. In this thesis, we integrate investment, retrofit and abandonment planning to analyse the economic trade off between abandoning oil and gas infrastructures and retrofitting them for hydrogen production and distribution (Zhang et al., 2023a). This has not been sufficiently studied in the existing literature.

2.4 Methodology

This section provides a concise literature review of the methodology relevant to this thesis, including MHSP, Benders decomposition, stabilisation methods and Lagrangean decomposition.

2.4.1 MHSP

Managing uncertainty is important in energy system planning. Although deterministic models have been used for energy system planning (Lara et al., 2018), stochastic programming models may be more useful in the current and future energy systems. Intermittent renewable energy, such as wind and solar, has higher penetration in the system. Dealing with uncertainty is important for the security of the supply of the system. Stochastic programming is one of the most important techniques to model uncertainty (Birge & Louveaux, 2011). An alternative but a rather conservative technique to model uncertainty is robust optimisation (Arrigo et al., 2022).

MHSP modelling approach was proposed to efficiently manage uncertainty in both short-term and long-term time horizons (Kaut et al., 2014). A similar study that formalised MHSP was presented in Escudero & Monge (2018). The main idea of MHSP is to disconnect operational problems between successive strategic nodes and embed them into their respective strategic nodes. This leads to a much smaller model than a traditional multi-stage stochastic programming model. For a long-term energy system planning problem, both short-term and long-term uncertainty can have a decisive impact on the optimal solutions. Long-term uncertainty includes CO_2 emission budget and energy demand. Short-term uncertainty is mainly time series parameters, including wind and solar capacity factors, hydropower production profile, demand profile, and oil and gas production profiles. Including uncertainty in both time horizons in a traditional multi-stage programming framework can lead to an explosion in the size of the scenario tree, and therefore to an intractable model. MHSP partially decouples the investment and operational nodes, significantly reducing the model size. It has been widely used for energy system planning problems (Zhang et al., 2022a; Durakovic et al., 2023b). Also, the bounds of MHSP have been studied (Maggioni et al., 2020).

Although MHSP was proposed to model investment planning model with long-term and short-term uncertainty more efficiently than traditional multi-stage stochastic programming, few if any application has included uncertainty in two time horizons. Part of the reason is that although MHSP leads to a smaller model than a multi-stage stochastic programming model, it is essentially a multi-stage stochastic program and can be hard to solve. The special structure of MHSP can be exploited for efficient decomposition algorithms, but there was no paper on the decomposition methods. Therefore, in this thesis, we exploit the structure of MHSP and propose two enhanced Benders decomposition (Zhang et al., 2022a, 2023a) and establish and propose enhanced Lagrangean decomposition algorithms for MHSP systematically (Zhang et al., 2023b).

2.4.2 Benders decomposition

Benders decomposition was initially proposed to solve MILP models with complicating variables (Benders, 1962). Benders decomposition separates the original problem into a master problem and one or more subproblems. The master problem usually contains integer decision variables and a subset of constraints, while the subproblems contain the remaining constraints and continuous variables. The algorithm iteratively solves the master problem and the subproblems, using the solutions of the subproblems to generate optimality or feasibility cuts that are added to the master problem. This iteration continues until an optimal solution is found.

Benders decomposition was widely used to solve stochastic programming models (Mitra et al., 2016). Van Slyke & Wets (1969) first applied Benders decomposition in the context of stochastic programming and solved two-stage stochastic programming linear programs with an L-shaped method.

Benders decomposition has been applied in transportation and logistics, energy and power systems, supply chain management, manufacturing, and facility location problems. Enhanced Benders decomposition is usually proposed to solve the underlying problem more efficiently than standard Benders decomposition. Oliveira et al. (2014) proposed accelerated Benders stochastic decomposition for optimisation under uncertainty of a petroleum product supply chain. A novel methodology for generating dynamically updated near-maximal Benders cuts was proposed for two-stage stochastic programming and compared with other acceleration techniques. A multi-cut Benders decomposition has been proposed for solving two-stage stochastic linear programming problems. The main idea was to add one cut per realisation of uncertain parameters. The multi-cut version has shown a significant reduction in computational time compared with standard Benders. A Monte Carlo simulation based algorithm that integrates a sample average approximation scheme with a Benders decomposition algorithm was proposed to solve stochastic uncapacitated hub location problems with stochastic independent transportation costs (Contreras et al., 2011). In this thesis, we apply enhanced Benders decomposition for solving large-scale energy system investment planning problems with short-term and long-term uncertainty (Zhang et al., 2022a, 2023a).

Since standard Benders decomposition was proposed, enhanced Benders decomposition algorithms have been proposed in the literature to improve the computational performance. For example, Mazzi et al. (2021) proposed a Benders decomposition with adaptive oracles to solve multi-stage stochastic programming problems, and demonstrated the algorithm on power system investment planning problems under several long-term uncertainties. Rodríguez et al. (2021) accelerated Benders decomposition using multiple techniques, including parallelising the algorithm and applications of special ordered sets, presolve and warm start. The proposed algorithm was applied to solve the short-term hydropower maintenance problem formulated as a two-stage stochastic program.

Some enhanced Benders decomposition methods have been proposed based on inexact information (Mazzi et al., 2021) and stabilisation (Zverovich et al., 2012). Mazzi et al. (2021) exploited the structure of the subproblem and proposed two adaptive oracles. The lower bound oracle approximated the objective function value from below, and the upper bound oracle provided a valid upper bound. The algorithm was shown to be 31.9 times faster than standard Benders decomposition. Zakeri et al. (2000) proposed inexact Benders decomposition that solved each subproblem up to a predefined tolerance, which was then tightened over time to ensure convergence. The generated cutting planes were all valid and asymptotically exact. In this thesis, we extend and improve the adaptive Benders decomposition in Mazzi et al. (2021). This is because MHSP falls into the class of problem that adaptive Benders can efficiently solve and adaptive Benders is a good starting point. Also, we notice that adaptive Benders cannot solve the proposed model efficiently due to two factors: (1) the proposed model is a multi-region planning problem and adaptive Benders oscillate much and find it hard to converge fast, and (2) in the proposed REORIENT model, there are integer variables in the reduced master problem. Therefore, we propose two alternative enhanced stabilised adaptive Benders to solve models efficiently (Zhang et al., 2022a, 2023a).

In addition to Benders decomposition, nested Benders decomposition has been proposed to solve multi-stage stochastic programming (Birge, 1985). Generalised Benders decomposition has also been proposed to solve mixed-integer nonlinear programming (Geoffrion, 1972).

The intersection of machine learning, artificial intelligence, and Benders decomposition is drawing research interest. Higle & Sen (1996) demonstrated the early application of artificial intelligence in the context of decomposition methods. Hooker (2012) showed how Benders decomposition could be integrated with artificial intelligence techniques, particularly constraint programming. A machine learning-enhanced multi-cut Benders decomposition approach was proposed to solve the transmission expansion planning problem under uncertainty (Borozan et al., 2023). The authors proposed to identify effective and ineffective cuts via supervised learning techniques, which reduced the number of cuts added to the reduced master problem. The reduction in computational time was not orders of magnitude. However, the potential of such a technique in other enhanced Benders such as the ones proposed in this thesis (Zhang et al., 2022a, 2023a) is worth investigating. The literature on Benders decomposition and machine learning is generally scarce but with potential for future growth.

2.4.3 Stabilisation methods

Stabilisation techniques are important in accelerating convergence, reducing oscillations, avoiding cycling and improving the robustness of decomposition algorithms. Oscillation can be a serious issue for Benders decomposition. The Benders master problem may become increasingly ill-conditioned after many iterations without converging. In this thesis, we focus on the trust region method and the level method. In the following, we present the related literature.

In many optimisation algorithms, like gradient descent, an approximation of the objective function is developed. Then a step is taken to reduce the value of this approximation, hoping that it will also reduce the objective function. However, the approximation may not be accurate over a large region. The further you are from where the approximation was built, the more likely the approximation is incorrect. The trust region method addresses this problem by defining a trust region around the current point, within which the model is trusted to be a reasonable approximation to the objective function. The algorithm then tries to minimise the model subject to the constraint that the step does not exit the trust region. If the step results in a significant decrease in the objective function, the size of the trust region is increased, while if the step does not lead to a decrease, the trust region is decreased.

The trust region method stabilises Benders decomposition by restricting the region of the variables to make smaller movements. The method was first developed in the context of the Levenberg-Marquardt algorithm. Later the trust region method has been further studied in Nocedal & Wright (2006). The performance of the trust region method can be highly dependent on their parameters. Gould et al. (2005) examined the sensitivity of trust region algorithms. A recommended range of parameter values was provided based on extensive numerical tests. However, the authors pointed out the range was for a specific type of problems and may not be suitable for other problems.

The level method stabilisation is the other approach we investigate. It was proposed in Lemarechal et al. (1995). The main idea of the level method stabilised Benders is to include an optimisation problem, after solving the reduced master problem, that minimises the distance moves from a reference point, and is subject to all the constraints from the reduced master problem and a level set constraint. The level set target is calculated based on the upper and lower bounds. An extensive computational benchmark for the methods, including Benders decomposition, stabilised decomposition, Benders decomposition with level method regularisation, and trust region stabilisation, has been presented in Zverovich et al. (2012).

In addition to stabilised Benders decomposition, the level method was also used to stabilise the outer approximation method to solve convex mixed-integer nonlinear programming problems (Kronqvist et al., 2020). Fabian (2000) and Zverovich et al. (2012) showed that the computational time was reduced significantly by stabilising the Benders decomposition with the level method. However, like other level method literature, the authors used a fixed stabilisation factor. Still, we observe that the performance of the level method stabilised Benders heavily depends on the choice of parameters. Therefore, we propose to address this issue and improve the robustness of the algorithm by including level set management steps which are analogous to adjusting the trust region in the trust region method (Zhang et al., 2022a, 2023a).

Another potential drawback of the level method algorithm is that if the reduced master problem is large, solving the stabilisation problem can take much time and lose the stabilisation value. In this case, we propose a centre point strategy for faster stabilisation (Zhang et al., 2023a).

2.4.4 Lagrangean decomposition

Lagrangean decomposition was proposed to solve problems with complicating constraints (Guignard & Kim, 1987). It is a special case of Lagrangean relaxation (Guignard, 2003). Lagrangean decomposition is different from Lagrangean relaxation because every constraint in the original problem appears in one of the subproblems. The bound predicted by Lagrangean decomposition is at least as tight as the one provided by Lagrangean relaxation (Guignard & Kim, 1987). In the context of stochastic programming, if a multi-stage stochastic programming problem is formulated in a scenario formulation with non-anticipativity constraint, one can decompose the problem using Lagrangean decomposition.

Scenario formulation leads to a larger monolithic model due to the duplication of variables from non-anticipativity constraints. Models based on scenario formulation can be decomposed by Lagrangean decomposition. Node formulation has a smaller monolithic model and can be decomposed by Benders decomposition. Both Benders and Lagrangean decomposition can utilise parallel computing. There are two non-obvious steps in Lagrangean decomposition: (1) constructing a feasible solution from the solutions obtained from the dual problems, and (2) updating the multipliers. Constructing feasible solutions is usually problem specific. Better multiplier updating schemes than the subgradient and cutting plane methods have been extensively studied (Mouret et al., 2011; Yongheng et al., 2014; Mulvey & Ruszczyński, 1995).

The literature shows that Lagrangean decomposition has been widely used for solving stochastic programming problems. The main idea of Lagrangean decomposition is to decompose the problems into scenario subproblems. Oliveira et al. (2013) proposed a Lagrangean decomposition approach for supply chain investment planning under uncertainty with risk considerations. The problem was formulated as a two-stage stochastic MILP problem. The multiplier updating procedure was improved based on the combination of cutting planes, subgradient and trust region strategies. In addition to solving two-stage stochastic programming, augmented Lagrangean decomposition was proposed for solving multi-stage stochastic programming (Mulvey & Ruszczyński, 1995). The main idea is to model the multi-stage stochastic programming using the scenario formulation and decompose the problem by scenarios. The advantage of scenario decomposition is that the subproblems can be solved in parallel.

There are other scenario decomposition algorithms. For example, a progressive hedging algorithm was proposed for stochastic programming problems with only continuous variables (Mulvey & Vladimirou, 1991). Although it has been proven that progressive hedging converges for linear programming, this is not the case for MILP. However, heuristic methods were proposed to tackle the problem with integer variables (Løkketangen & Woodruff, 1996), and the non-convergence issue of the heuristic was investigated in Watson & Woodruff (2011). In addition to the progressive hedging algorithm, dual decomposition was proposed for stochastic integer programming which achieved convergence compared with Løkketangen & Woodruff (1996) where convergence was empirically observed. Lagrangean decomposition is generally a more general algorithm compared with progressive hedging. Therefore, in this thesis, we focus on developing a parallel Lagrangean decomposition algorithm for MHSP.

The application of Lagrangean decomposition in MHSP has not been reported in the literature, and there is a special structure of MHSP that can be utilised to significantly speed up Lagrangean decomposition. In this thesis, we extend the literature by utilising the scenario formulation of MHSP, and propose paralleled Lagrangean decomposition with primal reduction to solve MHSP (Zhang et al., 2023b). The advantage of MHSP is that one only needs to impose non-anticipativity constraints on the investment decisions. This leads to fewer multipliers to update and potentially easier construction of a feasible solution. It is the first study to apply Lagrangean decomposition for MHSP. We also propose primal reduction to reduce the size of the primal problem after fixing the strategic variables and then solving the problem in parallel to reduce the computational time.

In addition to solving stochastic programming problems, Lagrangean decomposition can be applied to solve a large variety of problems. Mouret et al. (2011) proposed a new Lagrangean decomposition to solve a large-scale mixed-integer nonlinear program. A new hybrid dual problem was introduced to update Lagrangean multipliers that use cutting planes, subgradient and boxstep. A hybrid decomposition that combines bi-level and spatial Lagrangean decomposition methods was proposed to solve simultaneous scheduling and planning problems in a production-distribution network of continuous multi-product plants with temporal and spatial scales. Terrazas-Moreno et al. (2011) found that for multi-site, multi-period, and multi-product planning problems, temporal Lagrangean decomposition can obtain tighter bounds than spatial decomposition. Yongheng et al. (2014) proposed to decompose supply chain problems using Lagrangean decomposition based on warehouses. In this thesis, we propose Lagrangean-type decomposition to solve a long-term energy system planning problem with short-term and long-term uncertainty (Zhang et al., 2023b).

Chapter 3

Contributions

This chapter presents the contributions of the research presented in this thesis. The thesis consists of six papers that are enclosed in the second part of the thesis. For each paper, a summary is presented together with an overview of original contributions to research and their application to industry.

3.1 Papers

Paper I - Modelling and analysis of OEHs

Authors: Hongyu Zhang, Asgeir Tomasgard, Brage Rugstad Knudsen, Harald G. Svendsen, Steffen J. Bakker, Ignacio E. Grossmann

Published in Energy, Volume 261, Part A, 125219, 2022.

Clean OEHs may become pivotal for efficient offshore wind power generation and distribution. In addition, OEHs may provide decarbonised energy supply for maritime transport, oil and gas recovery, and offshore farming while enabling the conversion and storage of liquefied decarbonised energy carriers for export. In this paper, the role of OEHs is investigated in the transition of an offshore energy system towards a zero-emission energy supply. An MILP model is developed for investment planning and operational optimisation to achieve decarbonisation at minimum cost. We consider offshore wind, solar, energy hubs and subsea cables. A sensitivity analysis is conducted on CO_2 tax, CO_2 budget and power capacity from shore. The results show that OEHs can help reduce energy losses and costs.

My contributions to this paper include conceptualising the problem, developing and formulating the model, performing the programming and performing the analyses. Together with my co-authors, I have analysed and discussed the case study and results. Finally, I am the main author of the manuscript.

Paper II - OEHs in the decarbonisation of the Norwegian continental shelf

Authors: Hongyu Zhang, Asgeir Tomasgard, Brage Rugstad Knudsen, Ignacio E. Grossmann

Published in Proceedings of the ASME 2022 41st International Conference on Ocean, Offshore and Arctic Engineering, Volume 10: Petroleum Technology, V010T11A044, 2022

This paper studies the investment planning of a decarbonised Norwegian continental shelf energy system considering the connection and interfaces with the European energy system. A multi-horizon stochastic MILP model is developed for such a problem. We consider short-term uncertainties, including wind and solar capacity factors, energy load, platform production profiles, and hydropower production limits. Hydrogen-based energy hubs are considered onshore and offshore for potential renewable power generation, distribution and storage. The future hydrogen market or demand is not included in the model. The results show that OEHs are essentially wind power generation, conversion and distribution hubs, and that offshore grid design is important for decarbonisation by distributing wind power efficiently.

The model is extended based on the model developed in Paper I by including short-term uncertainty using MHSP and extending the model to European energy system planning. We notice the significant increase in computational time, motivating us for the solution methods described in Paper III.

My contributions to this paper include conceptualising the problem, developing and formulating the model, performing the programming and performing the analyses. I have analysed and discussed the case study and results with my co-authors. Finally, I am the main author of the manuscript.

Paper III - A stabilised Benders decomposition with adaptive oracles for large-scale stochastic programming with short-term and long-term uncertainty

Authors: Hongyu Zhang, Nicolò Mazzi, Ken McKinnon, Rodrigo Garcia Nava, Asgeir Tomasgard

Submitted to an international, peer-reviewed journal.

Benders decomposition with adaptive oracles was proposed to solve large-scale optimisation problems with a column-bounded block-diagonal structure, where subproblems differ on the right-hand side and cost coefficients. Adaptive Benders reduces computational effort significantly by iteratively building inexact cutting planes and valid upper and lower bounds. However, Adaptive Benders and standard Benders may suffer severe oscillation when solving a multi-region investment planning problem. Therefore, we propose stabilising Adaptive Benders with the level method and adaptively selecting the subproblems to solve per iteration for more accurate information. Furthermore, we propose a dynamic level method to improve the robustness of stabilised Adaptive Benders by adjusting the level set per iteration. We compare stabilised Adaptive Benders with the unstabilised versions of Adaptive Benders with one subproblem solved per iteration, and standard Benders on a multi-region long-term power system investment planning problem with short-term and long-term uncertainty.

My contributions to this paper include conceptualising the problem, developing the model and case studies, programming, formal analysis, and writing the manuscript. I am the main author of the paper.

Paper IV - Integrated investment, retrofit and abandonment planning of energy systems with short-term and long-term uncertainty using enhanced Benders decomposition

Authors: Hongyu Zhang, Ignacio E. Grossmann, Brage Rugstad Knudsen, Ken McKinnon, Rodrigo Garcia Nava, Asgeir Tomasgard

Submitted to an international, peer-reviewed journal.

We propose the REORIENT (REnewable resOuRce Investment for the ENergy Transition) model for energy systems planning with the following novelties: (1) integrating capacity expansion, retrofit and abandonment planning, and (2) using multi-horizon stochastic MILP with short-term and long-term uncertainty. We apply the model to the European energy system considering: (a) investment in new hydrogen infrastructures, (b) capacity expansion of the European power system, (c) retrofitting oil and gas infrastructures in the North Sea region for hydrogen production and distribution, and abandoning existing infrastructures, and (d) long-term uncertainty in oil and gas prices and short-term uncertainty in time series parameters. We exploit the special structure of MHSP, and propose an enhanced Benders decomposition to solve the model efficiently. We first conduct a sensitivity analysis on retrofitting costs of oil and gas infrastructures. We then compare the REORIENT model with a conventional investment planning model regarding costs and investment decisions. Finally, the computational performance of the algorithm is presented.

My contributions to this paper include conceptualising the problem, developing and formulating the model, performing the programming and performing the analyses. I have analysed and discussed the case study and results with my co-authors. Finally, I am the main author of the manuscript.

Paper V - Decomposition methods for MHSP

Authors: Hongyu Zhang, Èric Mor Domènech, Ignacio E. Grossmann, Asgeir Tomasgard

Submitted to an international, peer-reviewed journal.

MHSP is a modelling approach that has not been studied extensively compared with traditional multi-stage stochastic programming. In this paper, we exploit the structure of MHSP and show that such models can be decomposed by Benders decomposition and Lagrangean decomposition.

MHSP includes short-term and long-term uncertainty in investment planning problems more efficiently than traditional multi-stage stochastic programming. In this paper, we exploit the special structure of MHSP and formalise that it can be decomposed by Benders decomposition and Lagrangean decomposition. In addition, we propose parallel Lagrangean decomposition with primal reduction that (1) solves the scenario subproblems in parallel, (2) reduces the primal problem by keeping one copy for each scenario group at each stage, and (3) solves the reduced primal problem in parallel. We compare the parallel Lagrangean decomposition with primal reduction with the standard Lagrangean decomposition and standard Benders decomposition on a stochastic energy system investment planning problem. The computational results show that: (a) the Lagrangean type decomposition has better convergence at the first iterations compared with the Benders decomposition and (b) parallel Lagrangean decomposition with primal reduction is up to 9.2 times faster than standard Benders decomposition for a 1% convergence. Based on the computational results, the choice of algorithms for MHSP is discussed.

My contributions to this paper include conceptualising the problem, developing the model and case study, programming and performing the analyses. I am the main author of the manuscript.

Paper VI - Decarbonising the European energy system in the absence of Russian gas: Hydrogen uptake and carbon capture developments in the power, heat and industry sectors

Authors: Goran Durakovic, Hongyu Zhang, Brage Rugstad Knudsen, Asgeir Tomasgard, Pedro Crespo del Granado

A slightly revised version of this paper has been published in Journal of Cleaner Production, Volume 435, 140473, 2024.

This paper investigates the impact of the absence of Russian gas on decarbonising the European energy system. We focus on analysing the roles of hydrogen and carbon capture technologies in the European energy system up to 2060. In addition to the missing natural gas from Russia, we consider other natural gas supply chains, including liquified natural gas terminals and reserves in the North Sea and Northern Africa and the associated pipelines.

We extend the EMPIRE model to include sufficiently detailed modelling of heat and industry sectors to have endogenous hydrogen demand. This is valuable because the transition to a hydrogen-based system is less clear due to the energy reality in Europe. The extended model is the first model that includes power, heat and industry sectors in a single MHSP investment planning problem.

The results showed that the disruption of Russian gas imports has significant consequences on the decarbonisation pathways for Europe, with local energy sources and carbon capture and storage becoming even more important.

My contributions to this paper include conceptualising the problem, developing the model and case study, programming and performing the analyses. I am the second author of the manuscript.

3.2 Additional Contributions

In addition to publications, I have contributed to the research community by participating in conferences, including organising sessions and giving talks, teaching and research mentoring for master students, offering peer reviews for journals, and writing popular scientific articles.

Chapter 4

Concluding remarks and future research

In this PhD thesis, we have focused on: (1) developing optimisation models for long-term European energy system planning, and (2) exploring the special structure of MHSP and proposing efficient solution algorithms for solving large-scale multi-stage stochastic LP and MILP models.

In Paper I, we proposed the concept of OEHs for decarbonising the Norwegian continental shelf. We modelled the problem using MILP and analysed the value of OEHs in the energy transition. This paper gave a solid modelling foundation for the following papers. Paper II extended the model by including short-term uncertainty, and expanding the energy system to the European energy system. This paper further investigated the value of OEHs in the European energy system decarbonisation. We noticed computational difficulties in solving the model in Paper II, which motivated us to develop solution algorithms before extending the energy system model further. Therefore, in Paper III we proposed a dynamically stabilised adaptive Benders decomposition for solving large-scale LP and MILP problems with a column-bounded block diagonal structure. The algorithm was then applied to solve a UK power system planning problem formulated using MHSP. Also, the algorithm has significantly reduced computational requirements compared to existing solution methods. Paper IV contributed to both modelling and algorithm development. We have proposed the REORIENT model based on the models developed in Papers I, II and III. The novelty of the REORIENT model is that it integrates investment, retrofit and abandonment planning in a single optimisation model. Also, the REORIENT model considers uncertainty in both short-term and long-term time horizons, which the existing models do not include. In addition, we further developed the algorithm in Paper III and proposed a centre point stabilisation to reduce the effort on stabilising the adaptive Benders decomposition. Paper V formalised the decomposition methods for MHSP, and proposed parallelised Lagrangean decomposition with primal reduction. Paper VI used a different model, EMPIRE, and investigated the role of hydrogen and carbon capture and storage in power, heat and industry sectors in the context of decarbonising the European energy system without Russian gas.

The models and energy system case studies in this thesis have provided new insights for the European energy transition. To this end, a major contribution of the thesis is the model and methodology of Paper IV. Here, in addition to a generic model and solution method, new analyses were provided on how the North Sea may cut its infrastructure emissions while supporting the energy transition of the European energy system towards full decarbonisation. Also, the solution methods developed in this thesis have not only extended the existing operational research literature but also enabled us to solve large-scale energy system models and analyse the implications of the solutions for the European energy transition.

All the models developed in Papers I-VI can lead to applications. The REORIENT model in Paper IV includes all the novelties of the models in Papers I-III. In the future, the REORIENT model has the potential to provide more useful insights, such as to investigate the retrofit of existing oil and gas infrastructure for carbon capture and storage. In addition, future work may consider the European wide natural gas system in the REORIENT model to analyse the large-scale retrofit of the existing energy system for hydrogen production and distribution and CO_2 transportation and storage. Furthermore, the geographical resolution of the model can be increased for a more detailed analysis of the energy transition in a specific country and its interaction with the rest of the European energy system.

The REORIENT model can also be applied to investigate the decarbonisation of other regions such as offshore regions with high emissions including the Gulf of Mexico and the Brazilian continental shelf and other important onshore regions including the US, Chinese and African onshore energy systems. The model formulation of the REORIENT model is general and there are no case-specific constraints. Model parameters, constraints, and variables can be modified according to the specific problem of the study.

The REORIENT model can be improved by having more careful scenario-generation techniques. For example, generating scenarios for correlated long-term uncertain parameters such as oil and gas prices and hydrogen demand. For short-term time series uncertain parameters, techniques including machine learning can be used for the scenario generation to cover better different possible operational conditions. It is possible to link the REORIENT model with a machine learning based wind forecast model to better handle wind intermittency. Moreover, it may be beneficial to link the REORIENT model with other energy system models to integrate the novelties of different models for rigorous analysis of energy system decarbonisation.

On the methodology side, the stabilised adaptive Benders decomposition can be extended and improved in the future. We notice that for a very large problem with many decision nodes, the reduced master problem and the stabilisation problem may require prohibitive long solution time. Therefore, in future, techniques including node aggregation and cut selection may be needed to improve the performance. In addition, it is potentially beneficial to combine Lagrangean decomposition with adaptive Benders decomposition to solve huge scale MHSP efficiently. The adaptive oracles can also be used potentially in Lagrangean decomposition. Although MHSP reduces the problem size significantly, the model size may be reduced further by adjusting the scenario tree, e.g., removing the scenarios that do not make a difference, while solving the problem. In addition, MHSP can be extended to model endogenous uncertainty.

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Papers

Paper I

Modelling and analysis of offshore energy hubs

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Abstract

Clean offshore energy hubs may become pivotal for efficient offshore wind power generation and distribution. In addition, offshore energy hubs may provide decarbonised energy supply for maritime transport, oil and gas recovery, and offshore farming, while also enabling conversion and storage of liquefied decarbonised energy carriers for export. In this paper, the role of offshore energy hubs is investigated in the transition of an offshore energy system towards a zero-emission energy supply. A mixed-integer linear programming model is developed for investment planning and operational optimisation to achieve decarbonisation at minimum cost. We consider offshore wind, solar, energy hubs and subsea cables. A sensitivity analysis is conducted on CO_2 tax, CO_2 budget and the capacity of power from shore. The results show that: (a) a hard carbon cap is necessary for stimulating a zero-emission offshore energy system, (b) offshore wind integration and power from shore can more than halve current emissions, but offshore energy hubs with storage may be necessary for zero-emission production, and (c) at certain CO_2 tax levels, the system with offshore energy hubs can potentially reduce CO_2 emissions by 49% and energy losses by 10%, compared to a system with only offshore renewables, gas turbines and power from shore.

Keywords: Clean offshore energy hub, Sensitivity analysis, Deterministic mixed-integer linear programming model

I.1 Introduction

Offshore wind is an important pillar in the energy transition worldwide (International Energy Agency, 2020) to meet global and regional climate targets (European Commission, 2020a). Offshore Energy Hubs (OEHs) and the hub-and-spoke concept, offer a transnational and cross-sector solution for better harnessing offshore wind and integration with the rest of the energy system (North Sea ind Power Hub Programme, 2021). An energy hub is a physical energy connection point with energy storage where multiple energy carriers can be converted and conditioned (Geidl et al., 2007). This paper presents an optimisation model for the investment and operation of OEHs. It includes analyses of the functioning of OEHs in the transition of a large-scale energy system towards integrating more renewable energy. A case study is demonstrated in the North Sea as this region has huge potential for large-scale offshore wind (European Commission, 2020b) and hydrogen production.

The energy transition is widely studied (Piacentino et al., 2019). It includes research on the usage of both renewable energy technologies (Østergaard et al., 2021) and energy-efficient technologies (Vujanović et al., 2021). Transitioning to renewable energy, such as, wind, solar, and green hydrogen (Kovač et al., 2021), is a necessity for the decarbonisation of energy systems (European Commission, 2022). Green hydrogen produced from wind and solar power may play an essential role in the transition. Offshore regions with potentially abundant renewable energy sources are crucial for the global energy transition (Bosch et al., 2018). Therefore, we analyse the potential value of offshore renewable technologies for the energy transition of a regional offshore energy system and discuss how the study can be applied globally to contribute to the global energy transition towards zero emission.

The existing literature reviewed below shows that OEHs may be a promising option for producing green hydrogen offshore. The efficiency and cost analysis of OEHs has shown that an OEH is efficient and cost-worthy in electro fuel applications (Thommessen et al., 2021). However, the energy loss of a system with OEHs has not been considered. In this paper, we aim to analyse the potential value of OEHs in terms of energy losses. Producing green hydrogen offshore with OEHs and using the hub generated electricity to firstly cover the nominal electrolyser capacity may be cost competitive compared with current costs of grey and blue hydrogen (Singlitico et al., 2021). The energy storage function of OEHs has not been considered, which makes their OEH essentially a conversion and distribution hub. Offshore energy storage can be crucial because of the potential massive capacity (Scafidi et al., 2021). Therefore, in this paper, we consider OEHs with offshore hydrogen storage, see Figure I.1 for an illustration.

In addition to distributing offshore energy to onshore systems with OEHs, existing literature also investigates using OEHs for decarbonised energy supply for offshore industries (Dincer et al., 2021), including offshore oil and gas recovery (Zhang et al., 2017), maritime cargo transport, and offshore farming (Mikkola et al., 2018). The environmental value of OEHs has not been analysed in the literature. Cost estimation of electrifying offshore fields with OEHs is presented in Elgenedy et al. (2021). However, the cost data was not used for investment planning to analyse the trade-off of technologies. The value of OEHs for offshore sectors on a large scale is not sufficiently studied. Although green hydrogen is pointed out as promising storage that can provide supply security for oil and gas operations, it was not analysed.

To bridge the gaps mentioned above, we develop a multi-carrier Mixed-Integer Linear Programming (MILP) model for investment planning optimisation of an offshore energy system with a high degree of operational details. We model a clean OEH with hydrogen storage. We only consider producing green hydrogen from electrolysis. To analyse the economic advantages of OEHs compared with other technologies, we consider investments in offshore wind, offshore solar, OEHs and Power From Shore (PFS). The investment planning model is applied to an offshore energy system with the goal of decarbonising energy generation for offshore oil and gas installations in a given region. The oil and gas industry involves multi-billion-dollar investments and profits (Bret-Rouzaut et al., 2011) whose decarbonisation needs

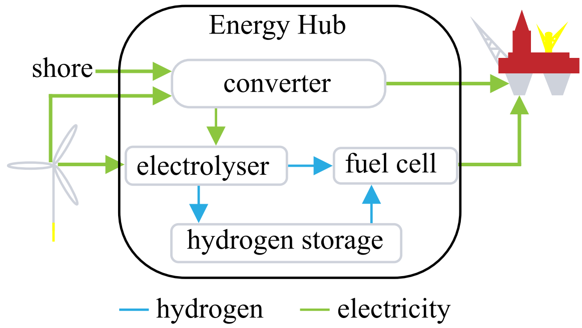

Figure I.1: Conceptual illustration of OEHs.

may trigger large-scale investments in OEHs. Offshore oil and gas is an important offshore sector in many countries, and the North Sea region has the highest number of offshore fields (Fazeres-Ferradosa et al., 2019). Therefore, studying the value of clean OEHs in the North Sea energy system may provide global insights.

The contributions of the paper are (1) an integrated investment and operational model with the following features, (a) OEHs are modelled for a large-scale offshore energy system, and (b) the hourly device-level energy consumption of platforms is modelled; (2) the value of OEHs is analysed in the North Sea offshore energy system transition towards zero-emission energy supply.

The outline of the paper is as follows: Section I.2 presents a literature review on energy system planning methods and OEHs and introduces the background regarding the production and decarbonisation of offshore oil and gas. Section I.3 gives the problem description followed by modelling strategies and assumptions. Section I.4 presents the MILP model and the case study. Section I.5 describes the case study and input data. Section I.6 presents the results and analysis of the case study. Section I.7 discusses the implications of the results and summaries the limitations of the research. Section I.8 concludes the paper and suggests further research.

I.2 Literature review

In this section, we review the literature on energy system planning methods and OEHs and give a background on the production process of offshore fields and corresponding decarbonisation issues.

I.2.1 Energy system planning methods

From an energy system planning perspective, the model in this paper is a bottom-up multi-carrier energy flow model. For an extensive review on this topic, we refer to Farrokhifar et al. (2020). Bottom-up energy system models represent the equilibrium of a part of the energy sector (Böhringer & Rutherford, 2008). On the other hand, top-down energy models try to depict the economy as a whole on a national level to analyse the aggregated effects of energy policies in monetary units. In this paper, we only use the bottom-up approach without considering the effect from a higher level using a soft-link or hard-link model because we are interested in the cost-optimal system design under different policy and technical scenarios rather than analysing its interaction with the macroeconomy.

For large-scale energy system planning problems, Linear Programming (LP) is usually used because of its computational tractability and sufficiency in modelling most investment and operational decisions and constraints. For example, energy system planning models like EMPIRE (Backe et al., 2022), and GENeSYS-MOD (Burandt et al., 2018) are LP models. Even though LP may be sufficient when dealing with very aggregated systems, for problems with lumpy investments (e.g. OEHs or transmission lines), LP cannot capture the economic scale of the investment decision, and MILP models are preferred (Lara et al., 2019). Mixed-integer nonlinear programming is also used in a planning problem to capture the system operations (Gupta & Grossmann, 2012). However, the computational difficulty may need to be addressed first to make the problem solvable. Our model uses MILP to provide more sensible investment decisions and avoid nonlinear constraints by simplifying the problem to reduce computational costs.

I.2.2 OEHs

The potential value and functioning of OEHs have drawn increased attention in several sectors. In the offshore oil and gas sector, it has been found that creating small energy hubs to import energy from various sources to offshore oil and gas platforms can achieve a massive reduction of CO_2 emissions in the UK continental shelf (Elgenedy et al., 2021). They mentioned that hydrogen energy storage is green and provides supply security for oil and gas operations. Energy-hub-based electricity system design for an offshore platform considering CO_2 mitigation is presented in Zhang et al. (2017). By verifying the proposed approach on an existing platform, it was found that CO_2 tax may play a decisive role in emission mitigation of offshore platforms. In addition to clean OEHs that utilise offshore wind, an OEH equipped with large gas turbines was proposed in Flórez-Orrego et al. (2021). Such an OEH serves as a centralised power generation system that offers higher efficiencies than simpler in situ gas turbines (Flórez-Orrego et al., 2021).

OEHs may allow for better harnessing of offshore wind to supply more stable energy to offshore oil and gas platforms in the short run and export clean energy to the continent in the long run. Connecting offshore wind in the North Sea via an artificial island and hub-and-spoke form was shown in Jansen et al. (2022) to be more economical than a traditional point-to-point connection if 10 GW offshore wind is built. Hydrogen-based OEHs also draw attention. An offshore artificial power-to-gas island can produce and transport hydrogen through natural gas pipelines (Gondal, 2019). Adding electrolysers to the offshore hub shows value in mitigating active power variations and maintaining the voltage of the hub (Marchand et al., 2021). Producing green hydrogen via OEHs to cover onshore energy demand and using hub generated electricity first to cover nominal electrolyser capacity may have better economic performance than producing hydrogen from natural gas (Singlitico et al., 2021). In addition, techno-economic analysis of offshore energy islands has shown that producing hydrogen offshore may be more beneficial than onshore production under some conditions. However, the development of offshore energy islands for electrical transmission and hydrogen production is not straightforward (van der Veer et al., 2019).

Studies have also been conducted on the impact of markets and the design of markets in a system with OEHs. The impact of the North Sea energy islands on national markets and grids is analysed in Tosatto et al. (2021) using a European electricity market model and a European electricity network model, where the authors found that social welfare increases but not for all the countries when the North Sea energy hub is included in the system. Moreover, a separate offshore bidding zone may lead to a more efficient offshore energy system with OEHs (Kitzing & González, 2020). We consider a smaller system and focus on the optimal capacities of new devices instead of analysing an extensive grid based on the assumption that a certain amount of capacity of an OEH will be added. The deployment plan for future European offshore grid development with an energy hub is analysed in Armeni et al. (2021). Unlike the study in this paper, they assume some scenarios of future deployment of wind turbines and transmission lines and analyse the system operation under different operational scenarios, including line fault, breaker failure, and bus bar fault. Compared with our study, they focus more on system operation under a predefined system configuration. We notice that in the study mentioned above, where the focus is on national markets, grid, and system failure, the investment planning and operations of OEHs are simplified. Therefore, we aim to contribute to more detailed modelling of optimising investment planning and operation of OEHs.

In addition to OEHs, more research has been conducted on the onshore energy system. The energy hub concept has been also used to increase the energy flexibility in buildings (Ottesen & Tomasgard, 2015) and electricity markets (Ødegaard Ottesen et al., 2016). Energy hub is a promising option for exploiting the benefits of multi-energy systems, such as coupled electricity and heating networks (Ayele et al., 2018), integrated natural gas and electricity (Jayasuriya et al., 2019) and electricity-thermal-natural gas coupling system (Wang et al., 2019). In addition, the design (Dolatabadi et al., 2017) and management (Najafi et al., 2016) of energy hubs with penetration of intermittent wind power has been studied using stochastic programming. Using energy hubs for coping with wind power volatility shows value in reducing operating cost, wind power curtailment and CO_2 emissions (Zare Oskouei et al., 2021). Energy hubs with power-to-gas and hydrogen storage can reduce emissions and produce hydrogen for end-use applications (Preston et al., 2020). Onshore energy hubs have much more versatile configurations and functioning compared to OEHs. We refer the readers to Mohammadi et al. (2018) and Mohammadi et al. (2017) for comprehensive reviews on the research works on energy hubs.

I.2.3 Offshore oil and gas fields

From the studies on offshore field production optimisation (Gunnerud et al., 2012) and offshore field infrastructure planning (Tarhan et al., 2009), we can see that platforms and fields vary a lot due to, amongst others, geological characteristics, reserves, and remaining lifetimes. In the following, we present a typical composition and production process of NCS platforms.

A North Sea field normally consists of topside structures and subsea production systems. A topside structure typically consists of a processing plant, a utility plant, drilling facilities, and a living quarter (Voldsund, 2014), see Figure I.2.

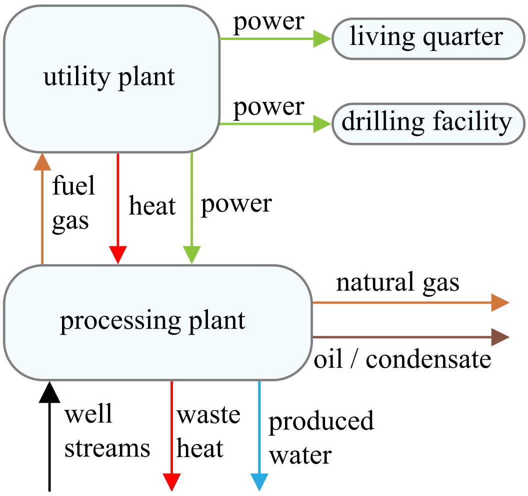

Figure I.2: Schematic of a topside structure of a typical North Sea oil and gas platform, adapted from Voldsund (2014).

The production plant receives and processes well streams. A visualisation of the production process is presented in Figure I.3. Major energy consumption takes place in production plants. The energy demand of production plants is conventionally fulfilled by gas turbines located in the utility plant. In 2014, gas turbines with waste heat recovery units covered approximately 90% of all heat demand for operations on the NCS (Mazzetti et al., 2014).

I.2.4 Decarbonisation of offshore fields

Norway was the world's third-largest exporter of natural gas in 2019 (Looney, 2020). Offshore oil and gas extraction was responsible for 26.6% (13.3 Mt CO_2 equivalent) of the total Norwegian greenhouse gases in 2020 (Statistics Norway, 2020b). Norway steps up its climate goal to reduce emissions by 50% – 55% by 2030 compared to 1990 levels (Ministry of Climate and Environment, 2020). Using OEHs to effectively exploit offshore wind power to decarbonise the NCS energy system may contribute to meeting Norway's and Europe's climate targets.

CO_2 tax is an important instrument for stimulating offshore energy system decarbonisation. In 2022, the tax is about 79 €/tonne in Norway (Sean Bray, 2022) with an ambition to increase it to 200 €/tonne by 2030 (Norwegian Petroleum Directorate, 2020a). In addition, the EU Emissions Trading System is a "cap and trade" system that also includes the emissions on the NCS (Norwegian Petroleum Directorate, 2020a). Carbon tax and the emissions trading system make a total carbon price of approximately 160 €/tonne. In this context, oil and gas companies are undertaking considerable investments in decarbonisation solutions to address climate goals, such as PFS and offshore wind. Oil and gas companies on the NCS have set climate targets. For example, Equinor (Equinor, 2021) and Vår Energy (Vår-Energi, 2019) aim to reduce greenhouse gas emissions by 40% by 2030, and near zero emission by 2050.

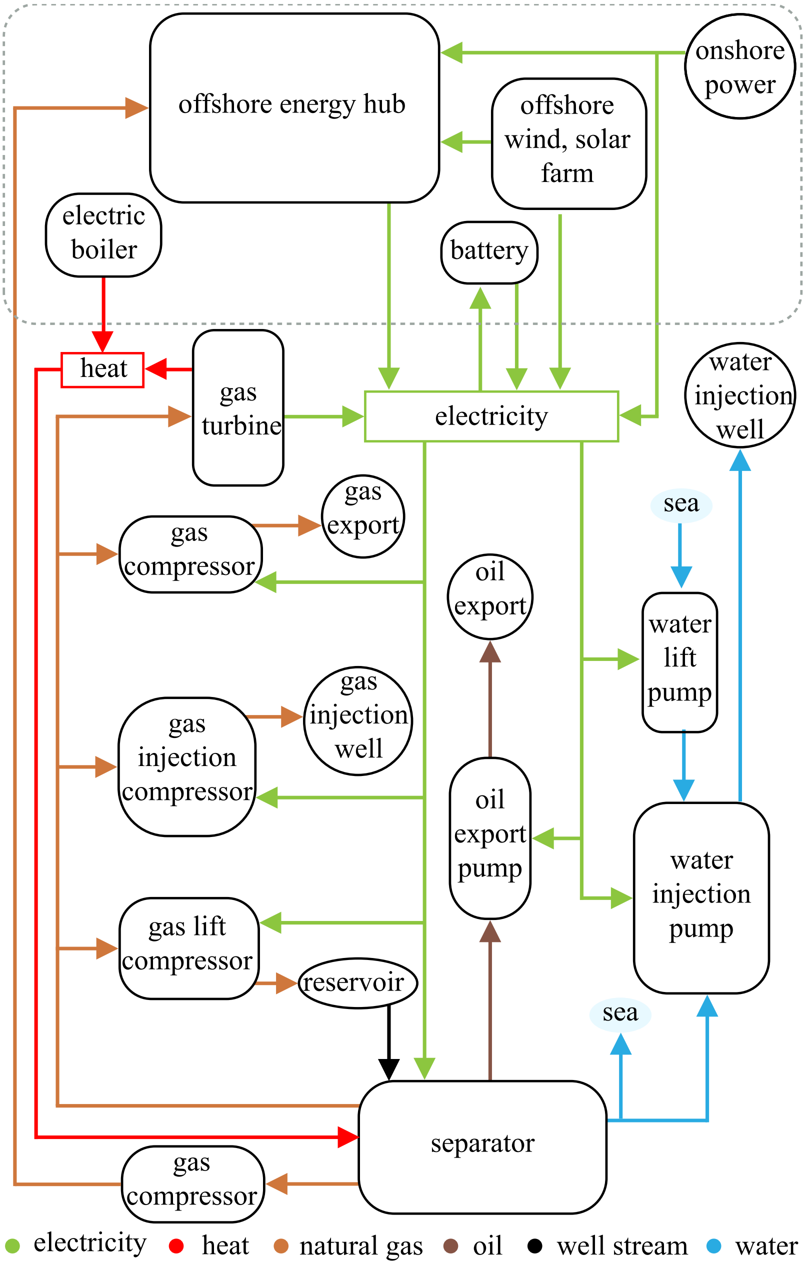
offshore energy hub
onshore power
offshore wind, solar farm
electric boiler
battery
heat
gas turbine
electricity
water injection well
gas export
gas compressor
sea
oil export
water lift pump
gas injection well
gas injection compressor
oil export pump
water injection pump
gas lift compressor
reservoir
sea
separator
gas compressor
electricity
heat
natural gas
oil
well stream
water

Figure I.3: Schematic of a potential decarbonised offshore field production process. A three-stage separator train separates well streams into produced water, oil, condensate and gas. Typically the first stage separator takes out most of the water and gas at arrival conditions. Fuel gas is taken from the first stage separator. The residual mix of oil, gas and water is heated before entering the second stage separator. Produced water is purified and discharged, and in some cases, reinjected into water injection wells to maintain reservoir pressure. Water lift pumps will lift seawater for reinjection if needed. Produced oil is pressurised by pumps and exported. Produced gas is used as fuel gas, compressed and exported, reinjected via dedicated wells for enhanced oil recovery or injected into the same wells for gas lift.
The grey dotted box includes the potential processes for decarbonisation. See Figure I.1 for a visualisation of the processes in an OEH.

Technologies for decarbonisation exist, and the question is to find the best mixture of such technologies at acceptable costs. There are four general approaches to reducing offshore CO_2 emissions, when maintaining a certain activity level:

(a) Reducing CO_2 emissions by improving reservoir drainage and processing energy efficiency (Bergmo & Grimstad, 2022). Water injection and gas injection are common reservoir drainage strategies used on the NCS. Pumping, compression and separation are major processes for handling produced fluids and gas in a processing system. Injection and processing account for more than half of the power consumption at the fields on the NCS.

(b) Increasing the energy efficiency of gas turbines. Due to the security of supply requirements, gas turbines usually operate with a margin, which leads to a low efficiency of around 33% (Lindegaard et al., 2014). Adding bottoming cycles to the existing gas turbines can improve their energy efficiency. However, unlike an onshore energy system, weight and space limitations of an offshore installation restrict extra devices like a bottoming cycle.

(c) Supplying zero emission or low emission energy to offshore oil and gas platforms. This includes PFS (Norwegian Petroleum Directorate, 2020b), switching fuel from natural gas to ammonia or hydrogen, and connecting offshore wind farms to platforms.

In the past years, several offshore fields have received PFS via HVDC/HVAC cables (Riboldi & Nord, 2017). In Norway, the cost of abating CO_2 emissions by taking PFS can vary from less than 100 to almost 800 €/tonne (Norwegian Petroleum Directorate, 2020c). Many abatement projects bringing PFS, are in their planning phase highly unprofitable even considering Norway's plan to increase CO_2 tax to 200 €/tonne in 2030. Besides, due to the capacity limits of the onshore system, the available power is limited in some cases.

Offshore wind is another technology to supply clean power to platforms. Equinor's Hywind Tampen project aims to be operational by 2022 (Equinor, 2020). The combination of an offshore platform with a wind farm represents a potentially good match for the offshore petroleum sector's desire for renewable energy with the offshore wind power industry's desire for an early market (Svendsen et al., 2011). The stability and control issues for an isolated offshore energy system consisting of a wind farm and five platforms were addressed in Svendsen et al. (2011). Integrating large wind turbines into a stand-alone platform is theoretically possible, but requires more operational and economic work to prove its feasibility (He et al., 2010). In Marvik et al. (2013), authors found that local wind power production for matching the offshore power demand improves both voltage- and frequency-stability in an offshore system. An MILP model for determining optimal offshore grid structures for wind power integration and power exchange named Net-Op was presented in Trötscher & Korpås (2011). An extension of Net-Op that takes into account investment cost, variability of wind/demand/power prices, and the benefit of power trade between countries/price areas is presented in Svendsen (2013).

(d) Deploying carbon capture and storage. Storing CO_2 in stable underground formations, e.g., old and stable oil reservoirs, has a relatively long history. Since 1996, nearly one million tonnes of CO_2 per year have been separated during the natural gas process from the Sleipner Vest field and stored in the Utsira formation (Norwegian Petroleum Directorate, 2020b).

The first two approaches have a limited impact on emission reduction, whereas the third and fourth approaches can give up to 100% reduction. We focus on supplying clean energy to offshore fields.

I.3 Problem description

First, this section introduces the proposed offshore energy system planning problem with OEHs. Then, we present the time and geographical structures with the aim of reducing computational time of a potentially large problem. Finally, we state the modelling assumptions.

The problem under consideration aims to make optimal investment and operational decisions for the NCS energy system with OEHs, based on the energy demand captured by the operational model. By solving such a problem, we aim to find out under what conditions OEHs may benefit the system and how OEHs operate with the rest of the system.

To model hourly energy demand, the following devices are considered: (a) separators; (b) pumps: water injection pumps, water lift pumps, oil export pumps; (c) compressors: gas injection compressors and gas export compressors. These devices have existing capacities, and no investment is made in them. Moreover, we assume that device efficiency, flow inlet/outlet pressures and hourly mass flow are given.

For the investments in decarbonisation solutions, we consider: (a) offshore renewable energies (offshore wind and offshore solar); (b) OEHs (electrolysers, hydrogen storage facilities and fuel cells); (c) subsea cables (HVAC, HVDC and offshore and onshore converter stations); (d) electric boilers; (e) platform located batteries. The capital expenditures, fixed operational costs are assumed to be known.

The problem is to determine: (a) capacities of decarbonisation technologies, and (b) operational strategies that include scheduling of generators, storage and approximate power flow among regions to meet the energy demand with minimum overall investment, operational and environmental costs.

I.3.1 Modelling strategies and assumptions

A multilevel control hierarchy was defined in Foss et al. (2018), arguing that the repetitive use of static models can solve many important petroleum production

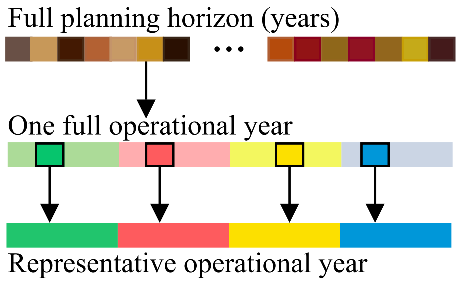

Figure I.4: Illustration of combined hierarchies, (adapted from van der Heijde et al. (2019)).

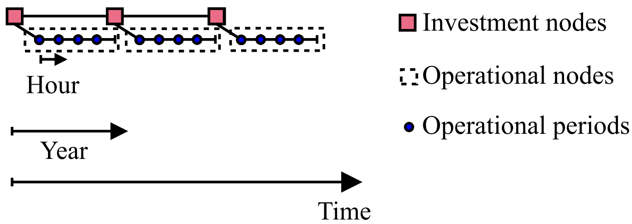

Figure I.5: Illustration of the linkage between investment planning and operational time horizon.

optimisation problems. A multi-period MILP model is developed for an integrated investment planning and operational problem that combines short-term and long-term control hierarchies. Aggregation, clustering and time sampling (Backe et al., 2021) are used to address the multi-time-scale aspects (Kaut et al., 2014) and solve a large-scale instance.

I.3.1.1 Time structure of the problem

The investment problem is optimised over a long-term horizon, e.g., a few decades. The operational problem is optimised on an hourly basis based on investment decisions. To combine these two control hierarchies without increasing much the computational time, N representative slices are selected, each containing h hours, and they are scaled up to represent a whole operational year. A visualisation of the time structure is in Figure I.4.

We use a node formulation to link investment planning with the system operation. An illustration of a planning problem is presented in Figure I.5. We define a point in time where investments are made as an investment node i_0. We then define the entire operational problem succeeding an investment node as an operational node i. Finally, the investment decision made in an investment node is examined by the operational node succeeding the investment node.

I.3.1.2 Geographical structure of the problem

The problem potentially consists of many regions, and we implement a k-means cluster method based on the locations of fields to reduce the problem size. There are two considerations when deciding the number of clusters. Firstly, we assume the OEH connects the surrounding fields via HVAC cables; thus, only fields with a feasible transmission distance (up to 100 km) are considered. Secondly, we assume that the cluster centres are the locations for OEHs. We prevent clusters with too few fields. For each cluster, we aggregate the individual fields into one larger field with a distance to the OEH equal to the average distance of the individual fields, and connect fields to OEH in hub-and-spoke form. Currently, we do not consider the interconnection among fields and clusters, resulting in reasonably simple network topology.

I.3.1.3 Assumptions

Each platform is assumed to be a typical North Sea platform with production processes as shown in Figure I.3. The energy consumption of pumps, compressors and separators can be formulated as a function of flow rate, pressure and temperature. For simplicity, the pressure levels and temperatures are assumed to take values that are typical on the North Sea, leading to a linear formulation. Kirchhoff voltage law is omitted, and replaced by an energy flow model. We assume no mass loss during production.

I.4 Mathematical model

This section presents a deterministic MILP formulated for the multi-carrier energy system investment planning problem with high degree of operational details. The model includes a long-term investment planning horizon and a short-term operational horizon. The integrated investment planning and operational model is partially based upon the linear programming model developed in Mazzi et al. (2021). Integer variables are used to improve the representation of the fixed capacity independent investment costs. The complete MILP problem consists of Equations (I.1)-(I.3).

The complete nomenclature of the model can be found in I.A. The supplementary definitions of some model parameters are presented in I.C. We use the conventions that calligraphic capitalised Roman letters denote sets, upper case Roman and lower case Greek letters denote parameters, and lower case Roman letters denote variables. The indices are subscripts and name extensions are superscripts. The same lead symbol represent the same type of thing. The names of variables, parameters, sets and indices are single symbols.

I.4.1 Objective function

$$\min c^{INV} + \kappa \sum_{i \in \mathcal{I}} c_i^{OPE} \tag{I.1}$$

The objective function, Equation (I.1), is to minimise the total investment (c^{INV}) and operational ($\kappa \sum_{i \in \mathcal{I}} c_i^{OPE}$) costs over the planning horizon.

I.4.2 Investment planning constraints

The investment planning constraints are given by:

$$c^{INV} = \sum_{i\in\mathcal{I}_0}\sum_{p\in\mathcal{P}}\left(C^{InvV}_{pi}x^{Inst}_{pi} + C^{InvF}_{pi}y_{pi}\right) + \kappa\sum_{i\in\mathcal{I}}\sum_{p\in\mathcal{P}}C^{Fix}_{pi}x^{Acc}_{pi} \tag{I.2a}$$

$$x^{Acc}_{pi} = X^{Hist}_{p} + \sum_{i\in\mathcal{I}_i} x^{Inst}_{pi}, \qquad p\in\mathcal{P}, i\in\mathcal{I} \tag{I.2b}$$

$$0 \le x^{Inst}_{pi} \le Q_p y_{pi}, \qquad p\in\mathcal{P}, i\in\mathcal{I}_0 \tag{I.2c}$$

$$0 \le x^{Acc}_{pi} \le X^{Max}_{p}, \qquad p\in\mathcal{P}, i\in\mathcal{I} \tag{I.2d}$$

$$y_{pi} \in \{0,1,2,...,Y_{pi}\}, \qquad p\in\mathcal{P}, i\in\mathcal{I}_0 \tag{I.2e}$$

$$x^{Inst}_{pi}, x^{Acc}_{pi} \in \mathbb{R}^{+}_{0}, \tag{I.2f}$$

$$y_{pi} \in \mathbb{Z}^{+}_{0}. \tag{I.2g}$$

The total cost for investment planning, Equation (I.2a), consists of actual investment costs (comprising capacity-dependent and capacity-independent costs), as well as fixed operating and maintenance costs. Here, κ is a scaling factor that depends on the time step between two successive investment nodes. Constraint (I.2b) states that the accumulated capacity of a technology x^{Acc}_{pi} in an operational node equals the sum of the historical capacity X^{Hist}_{p} and newly invested capacities x^{Inst}_{pi} in its ancestor investment nodes $\mathcal{I}_i$. The integer variable y_{pi} gives the number of units of technology $p\in\mathcal{P}$ in investment node $i\in\mathcal{I}_0$. Parameter Q_p represents the maximum capacity of a technology unit, and parameter X^{Max}_{p} denotes the maximum accumulated capacity of a technology. Parameter Y_p gives the maximum number of units that can be installed for the different technologies.

I.4.3 Operational constraints

We now present the operational constraints in one operational node i. Note that we omit index i in the operational model for ease of notation. Oil and gas recovery are modelled as this is the most likely use in the short to medium term. The operational constraints can be modified for other use, e.g., offshore fish farming, maritime, transport, and others.

$$
\begin{aligned}
c^{OPE} = \sum_{t\in\mathcal{T}_n} W_t \Bigg(\sum_{g\in\mathcal{G}} C^G_g p^G_{gt} + \sum_{z\in\mathcal{Z}} \sum_{l\in\{H,P\}} C^{Shed,l} p^{Shed,l}_{zt} + \\
\sum_{z\in\mathcal{Z}^O} \tau^{EP}_{zt} p^{PFS}_{zt} \Bigg) \qquad \text{(I.3a)}
\end{aligned}
$$

$$0 \le p_{pt} \le p^{Acc}_p, \qquad p\in\mathcal{P}^*, t\in\mathcal{T} \qquad \text{(I.3b)}$$

$$0 \le p^G_{gt} + p^{ResG}_{gt} \le p^{AccG}_g, \qquad g\in\mathcal{G}, t\in\mathcal{T} \qquad \text{(I.3c)}$$

$$0 \le v^{SHy}_{st} \le v^{AccSHy}_s, \qquad s\in\mathcal{S}^{Hy}, t\in\mathcal{T} \qquad \text{(I.3d)}$$

$$0 \le p^{SE+}_{st} \le \gamma^{SE}_s q^{AccSE}_s, \qquad s\in\mathcal{S}^E, t\in\mathcal{T} \qquad \text{(I.3e)}$$

$$0 \le p^{SE-}_{st} + p^{ResSE}_{st} \le \gamma^{SE}_s q^{AccSE}_s, \qquad s\in\mathcal{S}^E, t\in\mathcal{T} \qquad \text{(I.3f)}$$

$$0 \le q^{SE}_{st} \le q^{AccSE}_s, \qquad s\in\mathcal{S}^E, t\in\mathcal{T} \qquad \text{(I.3g)}$$

$$-p^{AccL}_l \le p^L_{lt} \le p^{AccL}_l, \qquad l\in\mathcal{L}, t\in\mathcal{T} \qquad \text{(I.3h)}$$

$$
\begin{aligned}
-\alpha^G_g p^{AccG}_g \le p^G_{gt} + p^{ResG}_{gt} - \\
p^G_{g(t-1)} - p^{ResG}_{g(t-1)} \le \alpha^G_g p^{AccG}_g, \qquad g\in\mathcal{G}, n\in\mathcal{N}, t\in\mathcal{T}_n \qquad \text{(I.3i)}
\end{aligned}
$$

$$-\alpha^F_f p^{AccF}_f \le p^F_{ft} - p^F_{f(t-1)} \le \alpha^F_f p^{AccF}_f, \qquad f\in\mathcal{F}, n\in\mathcal{N}, t\in\mathcal{T}_n \qquad \text{(I.3j)}$$

$$\sum_{g\in\mathcal{G}_z} p^{ResG}_{gt} + \sum_{s\in\mathcal{S}^E_z} p^{ResSE}_{st} \ge \sigma^{Res}_z P^{DP}_{zt}, \qquad z\in\mathcal{Z}^P, t\in\mathcal{T} \qquad \text{(I.3k)}$$

$$
\begin{aligned}
\sum_{g\in\mathcal{G}_z} p^G_{gt} + \sum_{l\in\mathcal{L}^{In}_z} \eta^L_l p^L_{lt} + \sum_{s\in\mathcal{S}^E_z} p^{SE-}_{st} + \sum_{r\in\mathcal{R}_z} R^R_{zt} p^{AccR}_r + \\
\sum_{f\in\mathcal{F}_z} p^F_{ft} + p^{ZO}_{zt} + p^{ShedP}_{zt} = P^{DP}_{zt} + \sum_{b\in\mathcal{B}^E_z} p^{BE}_{bt} + \sum_{e\in\mathcal{E}_z} p^E_{et} + \\
\sum_{l\in\mathcal{L}^{Out}_z} \eta^L_l p^L_{lt} + \sum_{s\in\mathcal{S}^E_z} p^{SE+}_{st} + p^{GShedP}_{zt}, \qquad z\in\mathcal{Z}, t\in\mathcal{T} \qquad \text{(I.3l)}
\end{aligned}
$$

$$
\begin{aligned}
\sum_{g\in\mathcal{G}_z} \eta^{HrG}_g p^G_{gt} + \sum_{b\in\mathcal{B}^E_z} \eta^{BE}_b p^{BE}_{bt} + p^{ShedH}_{zt} = \\
P^{DH}_{zt} + p^{GShedH}_{zt}, \qquad z\in\mathcal{Z}^P, t\in\mathcal{T} \qquad \text{(I.3m)}
\end{aligned}
$$

$$
\begin{aligned}
\eta^{EF}\Big(\sum_{f\in\mathcal{F}_z} H_t \rho^F p^F_{ft} - \sum_{s\in\mathcal{S}^{Hy}_z} v^{SHy-}_{st}\Big) = \\
\sum_{e\in\mathcal{E}_z} H_t p^E_{et} - \eta^{ES} \sum_{s\in\mathcal{S}^{Hy}_z} v^{SHy+}_{st}, \qquad z\in\mathcal{Z}^H, t\in\mathcal{T} \qquad \text{(I.3n)}
\end{aligned}
$$

$$H_t(p^{ResSE}_{st} + p^{SE-}_{st}) \le q^{SE}_{st}, \qquad s\in\mathcal{S}^E, t\in\mathcal{T} \qquad \text{(I.3o)}$$

$$q^{SE}_{s(t+1)} = q^{SE}_{st} + H_t(\eta^{SE}_s p^{SE+}_{st} - p^{SE-}_{st}), \qquad s\in\mathcal{S}^E, n\in\mathcal{N}, t\in\mathcal{T}_n \qquad \text{(I.3p)}$$

$$v^{SHy}_{s(t+1)} = v^{SHy}_{st} + v^{SHy+}_{st} - v^{SHy-}_{st}, \qquad s\in\mathcal{S}^{Hy}, n\in\mathcal{N}, t\in\mathcal{T}_n \qquad \text{(I.3q)}$$

$$\sum_{t\in\mathcal{T}_n} \sum_{g\in\mathcal{G}} W_t E^G_g p^G_{gt} \le \mu^E, \qquad \text{(I.3r)}$$

$$p_{lt}^{L} \in \mathbb{R}, \quad p_{gt}^{G}, p^{ShedP}, p^{ShedH}, p_{zt}^{PFS}, p_{pt}, p_{p}^{Acc}, p_{gt}^{G}, p_{bt}^{BE} \in \mathbb{R}_0^+, \tag{I.3s}$$

$$p_{gt}^{ResG}, p_{g}^{AccG}, p_{zt}^{GShedP}, p_{zt}^{GShedH}, v_{st}^{SHy+}, v_{st}^{SHy-}, v_{st}^{SHy}, p_{et}^{E} \in \mathbb{R}_0^+, \tag{I.3t}$$

$$v^{AccSHy}, p_{st}^{SE+}, p_{st}^{SE-}, p_{st}^{ResSE}, q_{s}^{AccSE}, q_{st}^{SE}, p_{l}^{AccL}, p_{r}^{AccR}, p_{ft}^{F} \in \mathbb{R}_0^+. \tag{I.3u}$$

The operational cost c^{OPE}, which is included in the objective function, Equation (I.1), for each operational node i, is described by Equation (I.3a) that includes total operating costs of generators $C_g^G p_{gt}^G$, energy load shedding costs for heat $C^{ShedH} p^{ShedH}$ and power $C^{ShedP} p^{ShedP}$ and electricity costs of onshore power $\tau_{zt}^{EP} p_{zt}^{PFS}$. C_g^G includes the variable operational cost, fuel cost and the CO_2 tax charged on the emissions of generator g. Constraint (I.3b) ensures that the devices including electric boilers $b \in \mathcal{B}^E$, electrolysers $e \in \mathcal{E}$, and fuel cells $f \in \mathcal{F}$ are within their capacity limits. Constraint (I.3c) dictates that the power generation of a gas turbine p_{gt}^G plus the spinning reserve p_{gt}^{ResG} must not exceed its capacity p_g^{AccG}. Constraint (I.3d) states that the hydrogen storage level v_{st}^{SHy} should be less than the capacity v_s^{AccSHy}. Constraint (I.3e) dictates that the power charged p_{st}^{SE+} should be within the charging capacity. Constraint (I.3f) specifies that the discharging power p_{st}^{SE-} plus the power for reserve requirement p_{st}^{ResSE} must not exceed the discharging capacity. Constraint (I.3g) limits the energy storage level q_{st}^{SE} to be within the capacity q_s^{AccSE}. Constraint (I.3h) shows that the power flow p_t^L is within the transmission capacity p_l^{AccL}. Constraints (I.3i) and (I.3j) capture how fast gas turbines and fuel cells can ramp up or ramp down their power output, respectively. The parameters α_g^G and α_f^F are the maximum ramp rate of gas turbines and fuel cells, respectively. The operating reserve requirement, Constraint (I.3k), dictates that the spinning reserve of gas turbines p_{gt}^{ResG}, plus the reserve of the electricity storage p_{st}^{ResES} must exceed the minimum reserve requirement, where σ^{Res} is a percentage of the power load. The power nodal balance, Constraint (I.3l), ensures that, in one operational period t, the sum of total power generation of turbines p_{gt}^G, power discharged from all the electricity storage p_{st}^{SE-}, renewable generation $R_{zt}^R p_{rt}^{AccR}$, fuel cell generation p_{ft}^F, power transmitted to this region, and load shed p_{zt}^{ShedP} equals the sum of power demand P_{zt}^{DP}, power consumption of electric boilers p_{bt}^{BE}, power consumption of all electrolysers p_{et}^E, power transmitted to other regions, and power generation shed p_{zt}^{GShedP}. The parameter R_{zt}^R is the capacity factor of renewable unit that is a fraction of the nameplate capacity p^{AccR}. The subset of a technology in region z is represented by $R_z := \{r \in \mathcal{R} : r \text{ is available in region } z\}$, where $\mathcal{R}$ can be replaced by other sets of technologies. The heat energy balance, Constraint (I.3m), states that the heat recovery of gas turbines $\eta_g^{HrG} p_{gt}^G$, plus electric boiler heat generation $\eta_b^{BE} p_{bt}^{BE}$, plus heat load shed p_{zt}^{ShedH} equals the heat demand P_{zt}^{DH} plus the heat generation shed p_{zt}^{GShedH}. The hydrogen mass balance, Constraint (I.3n), states that hydrogen produced by electrolyser equals the hydrogen injected into the storage v^{SHy+}, plus the hydrogen directly supplied to fuel cells . Constraint (I.3o) restricts the discharged energy and the energy for reserve purpose to be less than the energy storage level q_{st}^{SE}. Constraint (I.3p) states that the state of charge q_{st}^{SE} in period $t+1$ depends on the previous state of charge q_{st}^{SE}, the charged power p_{st}^{SE+} and discharged power p_{st}^{SE-}. The parameter η_s^{SE} represent the charging efficiency. The parameter H_t is the length of the period t. The hydrogen storage balance, Constraint (I.3n), shows that the hydrogen storage level v_{st}^{SHy} at period $t+1$ equals

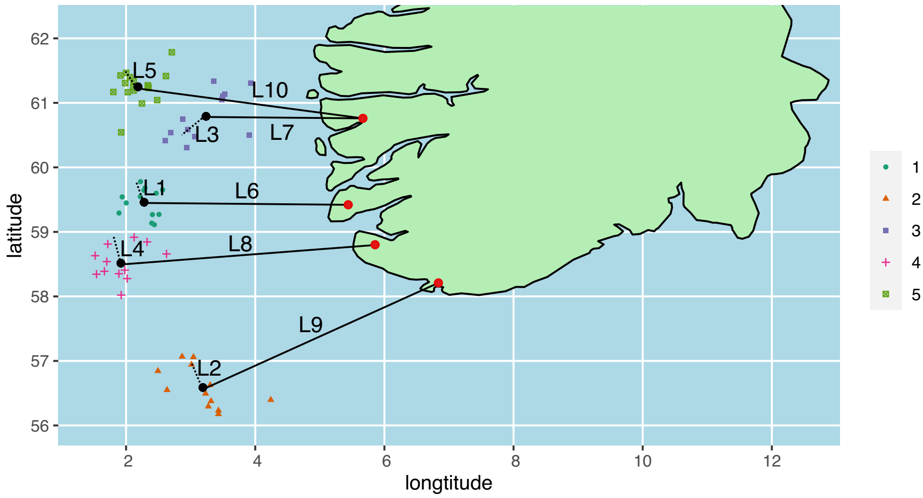

Figure I.6: Illustration of the NCS energy system with energy hubs. L1 – L5 (dotted lines) are representative HVAC cables, while L6 – L10 (solid lines) are HVDC cables. Black dots represent energy hubs and the red dots represent the onshore buses they connect to. Points with different shapes and colours represent NCS oil and gas fields.

to storage level at the previous period, plus the hydrogen injected v_{st}^{SHy+}, minus the hydrogen withdrawn v_{st}^{SHy-}. Constraint (I.3r) restricts the total emission. The parameter μ^E is the CO_2 budget. The symbol E_g^G is the emission factor per unit of power generated. The parameter W_t is the length of a period after scaling. We only consider emissions from the generators, but the model can easily be extended to include other emissions. The complete MILP problem consists of Equations (I.1)-(I.3).

I.5 Case study

The case study is carried out on the North Sea part of the NCS, considering 66 fields. The problem consists of 77 regions, divided into 66 fields, 5 OHEs and 5 onshore buses. By using the clustering approach described in Section I.3.1, the system can be represented using 5 clusters and henceforth go from 77 regions to 15 regions. The network topology is exemplified in Figure I.6. The power demand of platforms is assumed to be initially entirely supplied by gas turbines, as only a limited number of platforms receives PFS. Four representative months with hourly resolution are selected and scaled up to represent a whole year. In the case study, parameter Q_p is obtained from references. It is determined based on the nameplate capacity of devices. The parameter X_p^{Max} is set to a big number.

The field area geometry data is obtained from Norwegian Petroleum Directorate (2022). For each field, one coordinate is picked from the multipolygon as its representative location. The representative location, attributed cluster and the distance to its cluster centre for each field are summarised in Table I.2.

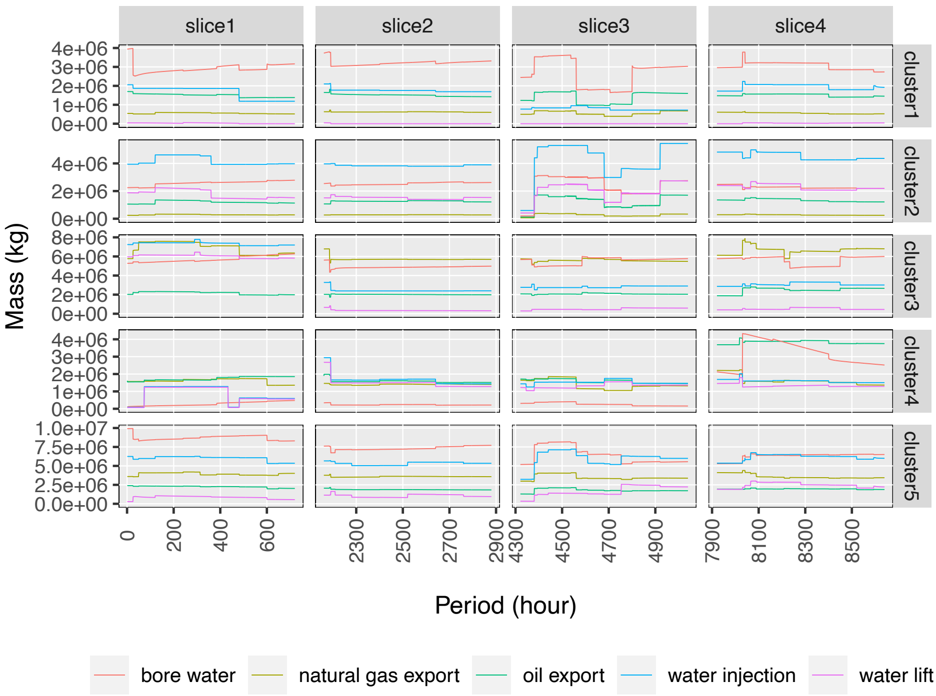

Figure I.7: Production profile in the representative months.

One month from each season is selected. The production of fields in each cluster is aggregated. A visualisation of the production data for each field in the four representative months is presented in Figure I.7, the data used for plotting is available at Zhang (2021).

The operational data in the oil and gas industry is sensitive, and usually not disclosed to the public. Aggregated data such as monthly or yearly production of petroleum on the NCS can be obtained from Norwegian Petroleum Directorate (2020b). One can also find monthly production and injection data for each field from Norwegian Oil and Gas Association (2021) and Norwegian Petroleum Directorate (2021). Neither of these can be directly used as inputs for this study due to the time resolution difference. Therefore, reasonable data generation is necessary. Raw data is collected from: (a) Norne (1998 – 2006) and Volve (2008 – 2016) fields with hourly production and injection data from The LowEmission Research Centre, SINTEF (2020), and (b) monthly production and injection data of each field from Norwegian Oil and Gas Association (2021). We develop a data generation method that considers the lifetimes of offshore fields (Zhang, 2021).

We define a base case (Base) with offshore renewables, electric boiler, battery and PFS as investment options. This case is then used as a benchmark to check against the case with OEHs. The full model given by Equations (I.1)-(I.3) takes approximately 2 hours to solve.

I.6 Results

We demonstrate the results of a static integrated investment planning and operational problem given by Equations (I.1)-(I.3), for a future point in time. The problem consists of $461,208$ continuous variables, 100 integer variables and $980,013$ constraints. The model was implemented in Julia 1.6.1 using JuMP (Dunning et al., 2017) and solved with Gurobi 9.1.2 (Gurobi Optimization, LLC, 2021). The code was run on a MacBook Pro with 2.4 GHz 8-core Intel Core i9 processor, with 64 GB of RAM, running on macOS 11.6 Big Sur. The Julia code and data for the case study have been made publicly available (Zhang, 2021). The integrated investment and operational model given by Equations (I.1)-(I.3) is solved to conduct sensitivity analysis on CO_2 tax, CO_2 budget and the capacity of PFS. The results show that a system with OEHs can reduce up to 49% CO_2 emissions and 10% energy loss compared with the one with only offshore renewables, gas turbines and PFS.

I.6.1 Energy system analysis

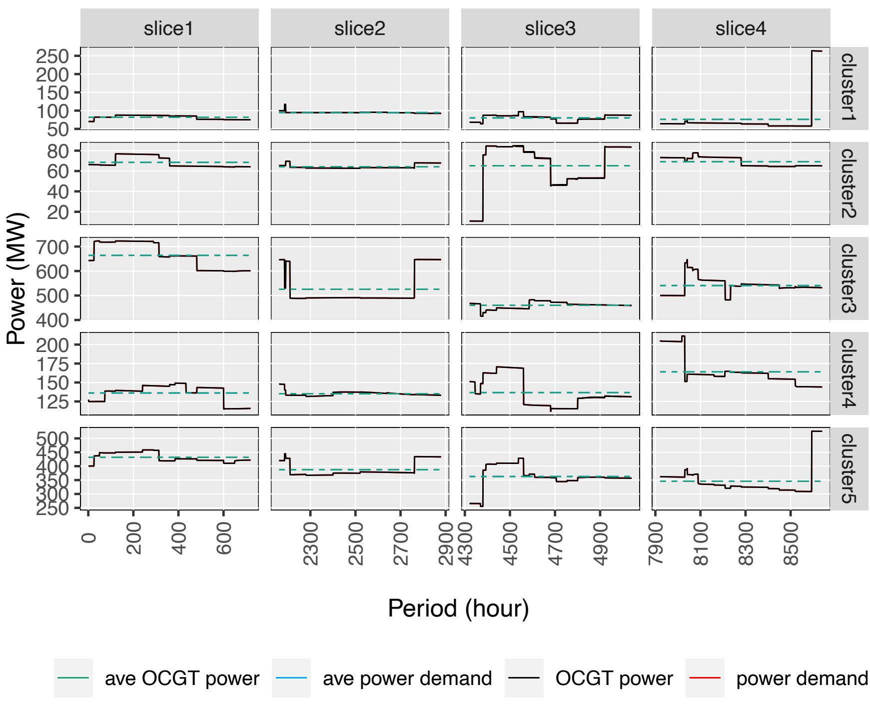

Figure I.8: Power consumption and supply (Only two lines are observable since power supply and demand match exactly. OCGT power equals power demand at all times).

In this section, we present results on energy consumption and CO_2 emission of the initial system. By post-processing, we verify the energy consumption of platforms is of the same order of magnitude as the reported numbers. The resulted CO_2

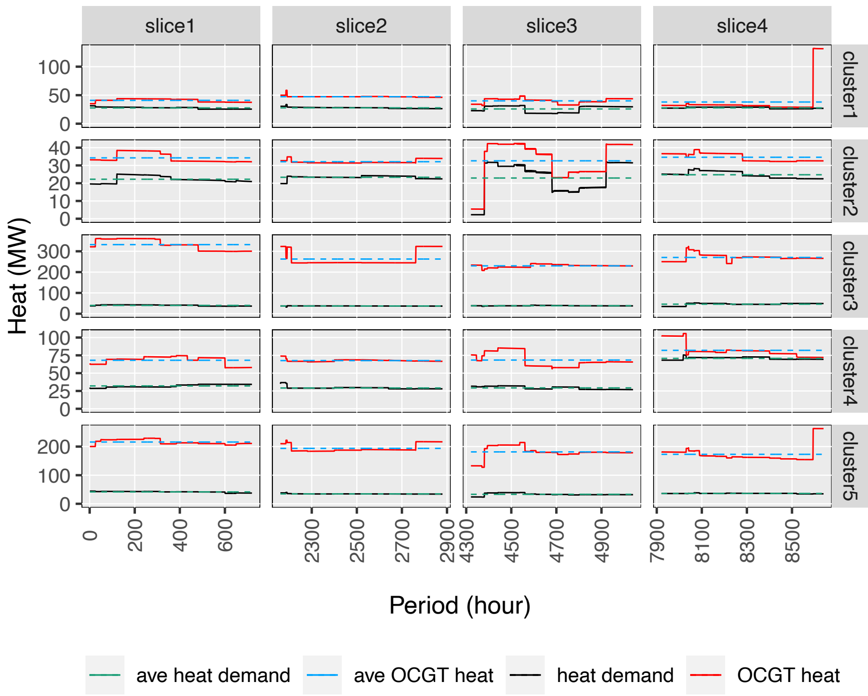

Figure I.9: Heat consumption and supply.

emission is 5.54 Mt/yr. In comparison, the reported total emission of the relevant fields was 6.89 Mt in 2019 (Norwegian Petroleum Directorate, 2021). The emissions from the model are expected to be lower than 6.89 Mt since not all emission sources are considered. Based on Nguyen et al. (2014), one could assume that the major processes considered in this study make up about 80% of the total load. Therefore, 5.54 Mt yearly emission is within the correct range, implying that the energy load modelling is relatively accurate.

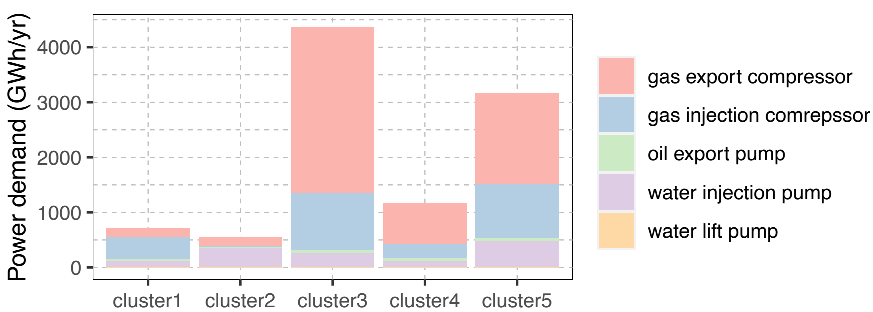

Figure I.10: Power demand in a year.

	cluster1	cluster2	cluster3	cluster4	cluster5
Emission distribution	6.8%	5.5%	44.8%	11.7%	31.2%

Table I.1: Emission distribution by cluster.

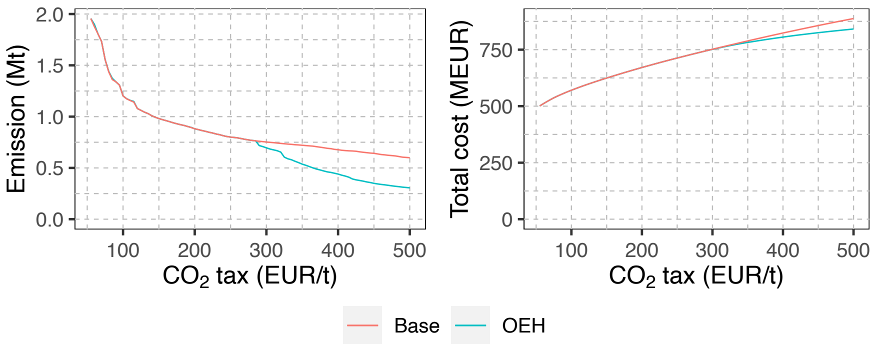

Figure I.11: Emission and cost comparison (CO_2 tax sensitivity analysis).

From Figure I.8, we can see that the power output of the Open Cycle Gas Turbine (OCGT) matches the power demand at every operational period. Heat recovery of OCGTs is assumed to be the only heat source. Figure I.9 shows that heat recovery of OCGTs provides more than enough heat due to high electricity generation. We can also see that energy consumption can vary significantly. A breakdown of electricity load is shown in Figure I.10, gas export compressors dominate the power consumption in clusters $3-5$. Water injection is the largest power consumer in cluster 2 since there are some mature fields (e.g., Ekofisk) whose reservoir pressures are mainly maintained by water injection. OCGT is the only energy and emission source in the initial setup. Therefore, emission breakdown includes the emissions from the total energy consumption of each region. Cluster 1 has the second smallest share of the total energy consumption, with a considerable amount of power consumed by gas injection. The fields in cluster 1, such as Grane, have the third-highest gas injection level among the 66 fields. From Table I.1, we find that emission mainly comes from the northern part of the North Sea.

I.6.2 Sensitivity analysis of CO_2 tax

This section presents the results of sensitivity analysis of CO_2 tax. We introduce CO_2 tax and still keep the carbon budget inactive. We increase the carbon tax from 55 to 500 €/tonne with a step size of 5 €/tonne. PFS capacity limits are estimated from Norwegian Petroleum Directorate (2020c) and Statistics Norway (2020a). Note that the cost of PFS may be underestimated since we only consider the costs of subsea cables, onshore and offshore converter stations and electricity bills. In reality, PFS projects may also involve investment in onshore transmission lines or onshore power system capacity expansion. We analyse the results from three metrics: cost, CO_2 emission and energy loss. Energy losses are from conversions, transmission, and generation shed. The calculation is presented in I.B.

From Figure I.11, we can see that CO_2 tax as a single instrument may not

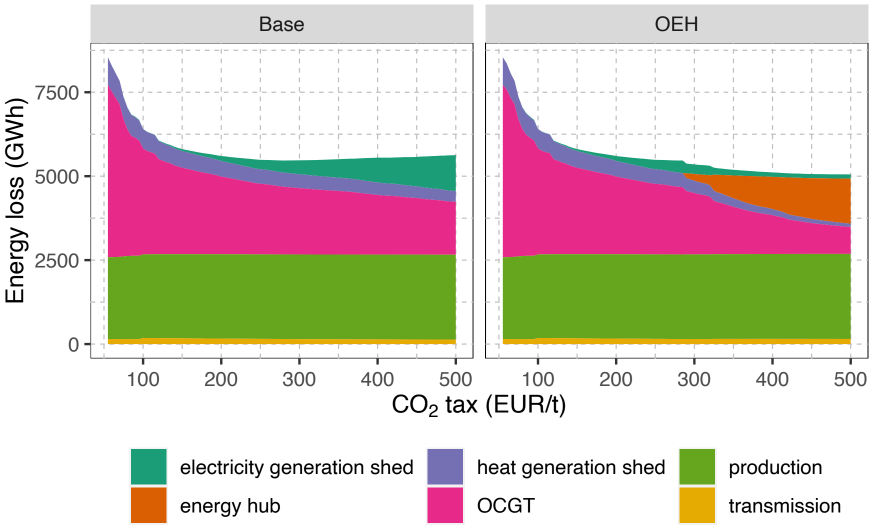

Figure I.12: Energy loss (CO_2 tax sensitivity analysis).

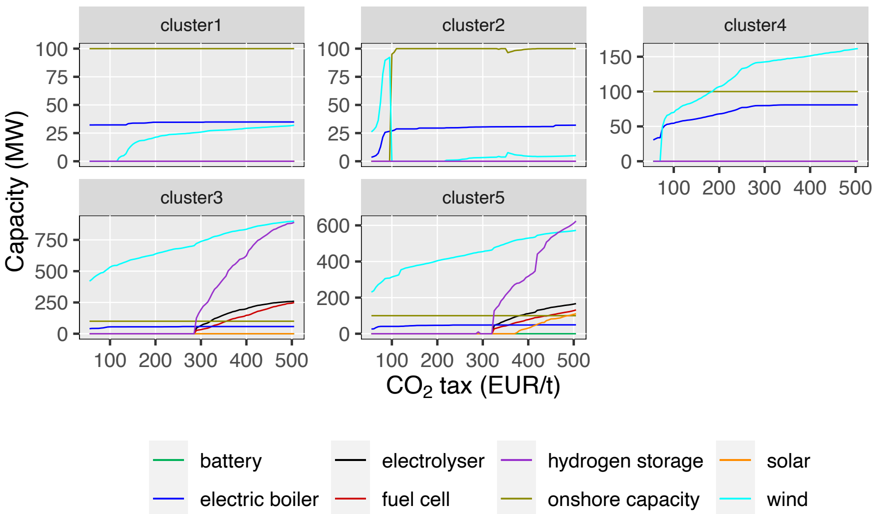

Figure I.13: Capacities of technologies in each cluster (CO_2 tax sensitivity analysis), hydrogen storage is measured in tonne.

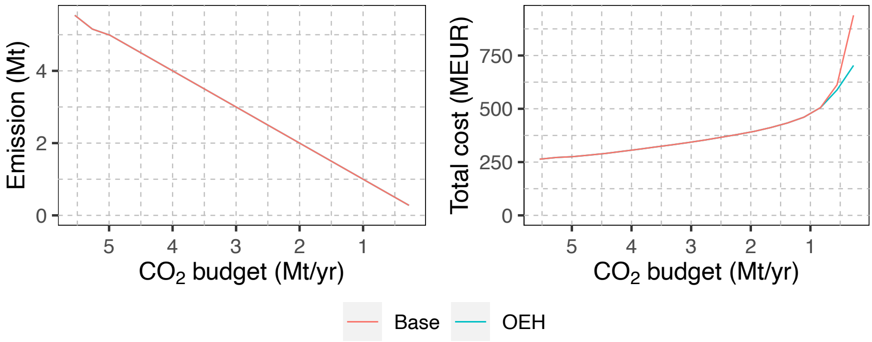

Figure I.14: Emission and cost comparison (CO_2 budget sensitivity analysis).

be enough to yield a zero emission system. We also find that near zero emission can be achieved with a very high CO_2 tax. Therefore, a hard carbon cap may be necessary for stimulating a zero emission system. When CO_2 tax is 55 €/tonne, the system reduces about 65% of the emissions compared to the initial 5.54 Mt/yr emission. Approximately 84% of the emissions can be cut if CO_2 tax is increased to 200 €/tonne as planned. As OCGTs are replaced by renewable energy, energy loss is reduced as well. OEHs can potentially reduce up to around 49% more CO_2 emission, and 5% total cost than the case with only offshore wind and PFS (Base) at certain CO_2 tax levels. From Figure I.12, we find that energy loss during production accounts for 11% of the energy loss. OCGTs lose 18 GWh of energy during an operational year. As production from wind turbines replaces gas turbines, energy loss from OCGT is reduced. However, due to the lack of energy storage, electricity generation shedding increases because wind power is shed. We find that OEHs can effectively reduce electricity generation shedding, although it loses energy during conversion. Overall, energy loss is up to 10% lower in the case of OEHs compared with Base at certain tax levels.

From Figure I.13, we find that different clusters show different levels of sensitivity to CO_2 tax. Offshore wind is the first renewable energy solution that is added to the system. Electric boilers are needed as offshore wind replaces gas turbines partially. OEHs are installed when CO_2 tax is above 290 €/tonne. Offshore solar is only added in cluster 5 under very high CO_2 tax levels. OCGTs still operate even CO_2 tax increases to 500 €/tonne. We can see that in a static planning problem, if CO_2 tax is the only instrument and increases to 200 €/tonne as the government's plan in 2030, OEHs may not be necessary. However, CO_2 tax combined with the EU emissions trading system may likely increase the total CO_2 price to around 250 – 300 €/tonne, which is about the breakeven price of OEHs. In addition, the potential benefits of the OEHs may realise once they provide services to more sectors, such as exporting hydrogen for industries or transportation.

I.6.3 Sensitivity analysis of CO_2 budget

For the CO_2 budget, we use initial emissions as the starting point, and reduce it by 5% until it hits 0. From Figure I.14, we find that the carbon cap is binding most of the time, and we rarely see that emissions are reduced more than the carbon cap.

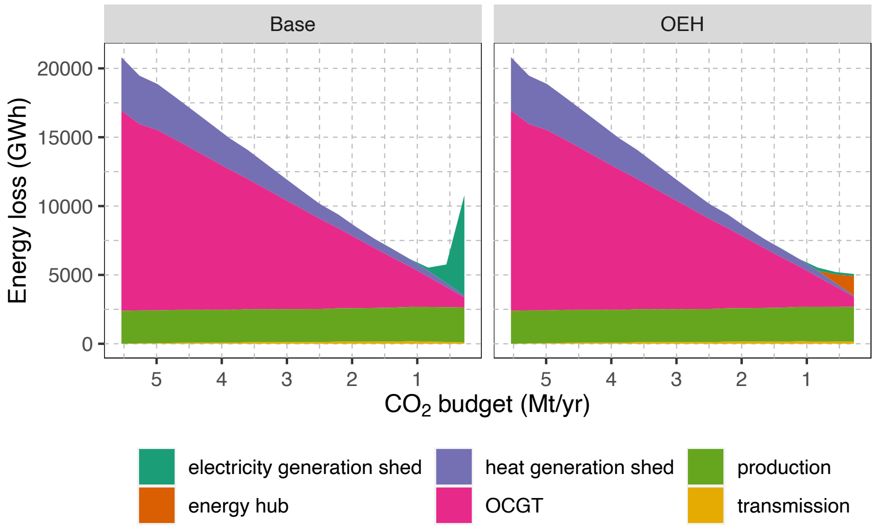

Figure I.15: Energy loss (CO_2 budget sensitivity analysis)

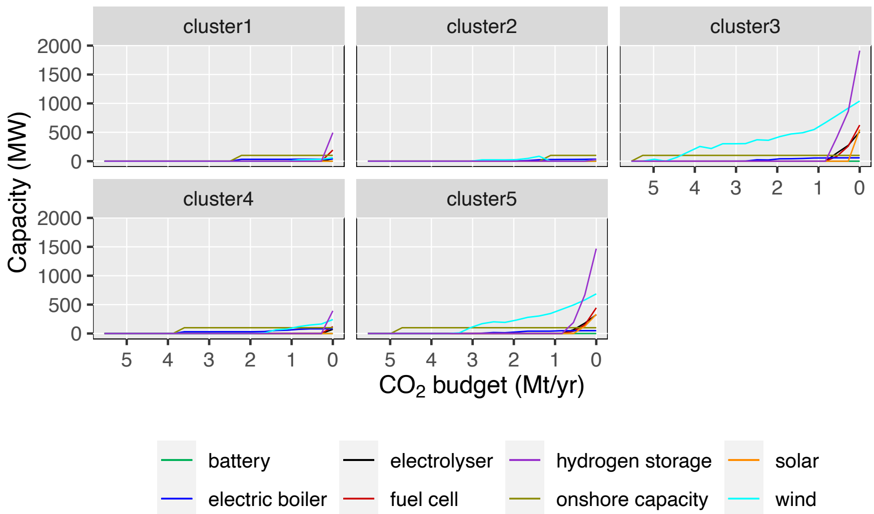

Figure I.16: Capacities of technologies in each cluster (CO_2 budget sensitivity analysis), hydrogen storage is measured in tonne.

Thus, there is no difference in actual emissions in Base and the system with OEHs. However, the cost is 25% lower in a zero emission system with OEHs compared with Base.

We find that in a zero emission system without OEHs, energy loss is around 530 TWh due to 90 GW of wind power capacity and 15 GW offshore solar capacity without storage. This may not be likely to happen since some forms of storage would be added to compensate for offshore wind in reality. From Figure I.15, we can see a large amount of energy loss when reaching near zero emission system in Base. The energy loss in Base is 10,749 GWh in a near zero emission system, which is about twice as high as for the case with OEHs. A large amount of wind power is installed to meet power demand at any time. Therefore, the same capacity of wind that can cope with peak demand hours, will also generate surplus power during normal hours. This leads to increased energy losses as more wind replaces OCGT without proper energy storage. In the case of OEHs, wind power can be stored when excess power is generated. It is also worth noticing that in the energy system without an OEH, energy storage is the battery on the platforms, which can be infeasible due to space and weight limitations. We observe that investments in batteries are only needed when approaching zero emission in Base. No battery is needed in a system with OEHs. In addition, the energy loss of OEHs is 28% of the total loss, and the loss during production is about 50% of the total.

From Figure I.16, we find that cluster 3 receives PFS after a 5% reduction of the carbon cap. Cluster 3 has the highest emission level but the shortest distance from shore. Therefore, taking PFS and partially electrifying the fields in cluster 3, can help the system reduce 5% of the emissions in a cost efficient way. The system does not cut emissions proportionally in each cluster, but cuts emissions from clusters with the highest emission, such as cluster 3 and cluster 5. Therefore, it may be necessary to consider the whole NCS when conducting system planning, rather than consider each cluster separately and reach sub-optimality. Cluster 2 is the most remote, more than 300 km from shore; PFS is less economical than offshore wind. Therefore, offshore wind is added to cluster 2 when the carbon cap drops to 2.77 Mt/yr. When the CO_2 budget reduces to below 0.83 Mt/yr, CO_2 emissions are nearly zero in clusters 1 and 2. However, the carbon cap needs to reduce to zero to shut down OCGTs completely in all clusters. Nearly $4,295$ tonnes of hydrogen storage capacity is needed in a zero emission NCS energy system, and nearly half is installed in cluster 3.

I.6.4 Sensitivity analysis of the capacity of PFS

We now present the results of sensitivity analysis of the capacity of PFS. The capacity of PFS affects the investments in offshore technologies. An onshore system has a limited capacity to transmit power offshore. Although, onshore system expansion can affect this capacity limit, it is not considered directly in this paper. Therefore, we conduct sensitivity analysis to reveal the relationship between onshore power system capacity and offshore decarbonisation technologies.

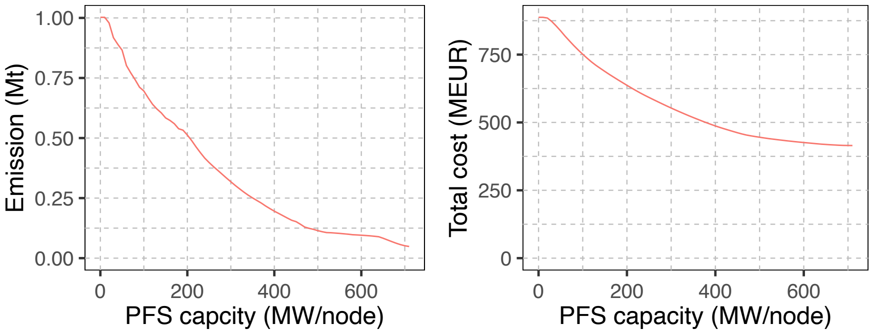

Figure I.17: Emission and cost (PFS capacity sensitivity analysis, S1).

I.6.4.1 Scenario 1 (S1)

The first scenario is to fix the CO_2 tax to 300 €/tonne, and increase the PFS capacity of each onshore location from 0 MW to 1000 MW with a 10 MW step. The investment decisions remain the same when the PFS capacity is higher than 710 MW. Therefore, we only present the results from 0 MW to 710 MW. From Figure I.17, we can see that by having 710 MW capacity in each onshore location, the system can achieve 0.01 Mt/yr emission and reduce about 53% of the total cost. However, increasing the capacity further does not cut emissions or costs further. Figure I.19 shows that energy loss during transmission makes up 16% of the total energy loss as we increase the onshore capacity. Electricity generation shed decreases as onshore capacity increases because PFS gradually replaces offshore wind, and less energy is lost from wind turbines. From Figure I.18, we find that for onshore locations that connect to cluster 1 and cluster 2, the needed onshore capacities are about 126 MW and 108 MW, respectively. There are also upper limits on the installed capacity of PFS in the other clusters. We also notice that OEHs are still needed in clusters 3 and 5 as we increase the onshore capacity. However, eventually, OEHs are not needed since PFS can provide more stable power and OEH with storage becomes less important.

I.6.4.2 Scenario 2 (S2)

In the second scenario, the CO_2 tax is fixed to 400 €/tonne. We increase the onshore capacity from 0 MW to 1000 MW, and present the results until 770 MW. From I.20, we can see that without PFS, the system can achieve 0.63 Mt/yr emissions under S2 condition. Increasing the onshore capacity brings down 57% of the cost and also cut emission further to near zero. Figure I.22 shows that about 22% of the energy loss is from OEHs initially. OEHs are not needed when the onshore capacity increases to around 390 MW for each location. By adding the installed PFS capacity shown in Figure I.21, we find that a total onshore capacity of 1.74 GW may help the offshore energy system achieve near zero emission. We notice that the onshore system needs to provide an averagely of 1.4 GW. By checking the average power transmission of PFS, which might not be feasible without onshore system expansion.

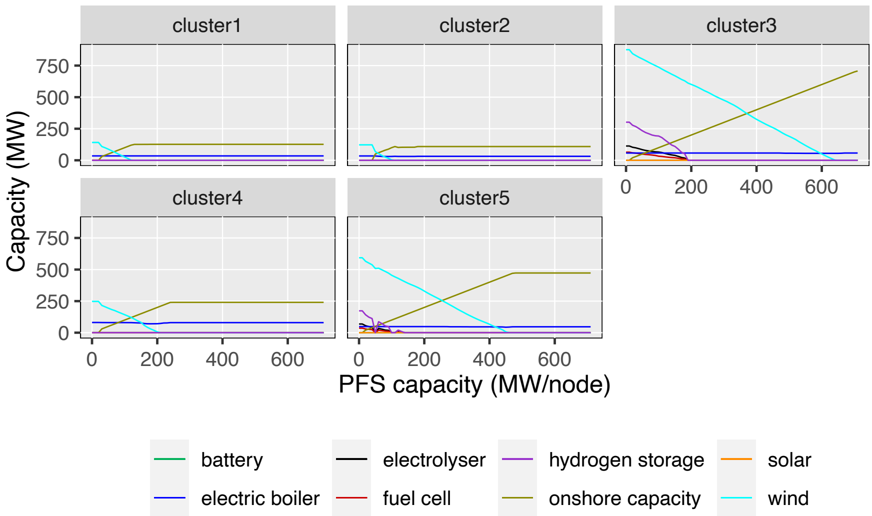

Figure I.18: Capacities of technologies in each cluster (PFS capacity sensitivity analysis, S1), hydrogen storage is measured in tonne.

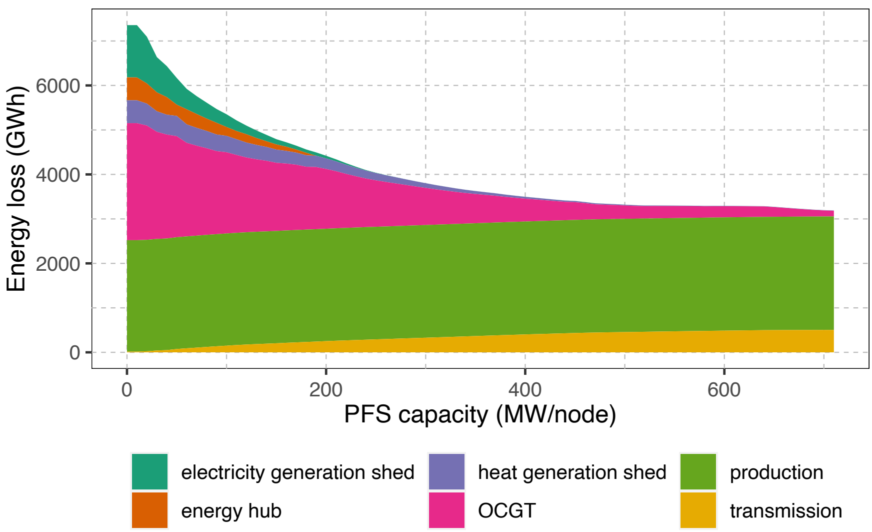

Figure I.19: Energy loss (PFS capacity sensitivity analysis, S1).

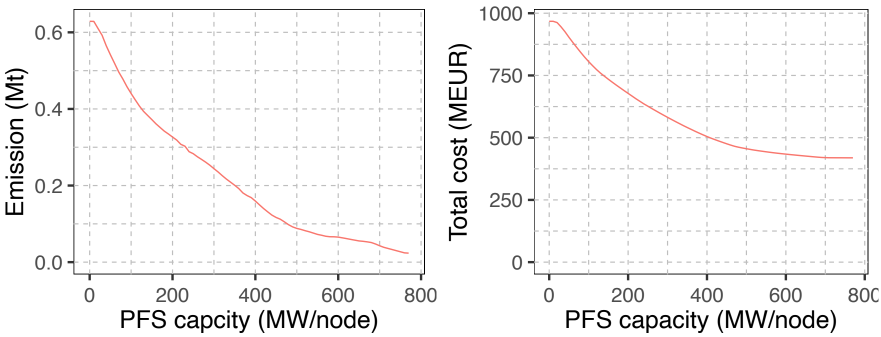

Figure I.20: Emission and cost (PFS capacity sensitivity analysis, S2).

I.7 Discussion

The analysis above shows that OEHs have potential value in emission reduction, energy losses and costs. The operational part of the model provides energy consumption of fields that is consistent with the analysis in Nguyen et al. (2014), and aligned with officially reported numbers (Norwegian Petroleum Directorate, 2020b). However, a similar investment planning problem is not found in the literature. Therefore, the results from the paper may provide a possible benchmark for future studies.

We demonstrate the case study on the NCS energy system. A unique characteristic of the NCS is that PFS is nearly emission free because nearly all Norwegian onshore power production is based on hydro power. However, in many regions, there may be less intention to use PFS because of the carbon intensity of the onshore power. In such a case, using PFS to compensate for offshore wind volatility may be infeasible, and hydrogen production and storage may become more relevant. This may affect the optimal investment planning of the system.

Based on the optimal solutions under different conditions showed in Figures I.13,I.16,I.18 and I.21, we notice that offshore wind is a relatively cost efficient technology that can achieve moderate emission targets of platforms. This may suggest that in countries where PFS is not an option, offshore wind alone can still help emission reduction to a large extent.

In addition, the results suggest that producing and storing hydrogen offshore in OEHs proves to be economical under a strict carbon budget and a high CO_2 tax. One reason is that PFS is considered as an option for decarbonisation, and building cables is most likely cheaper than building an OEH. However, taking PFS will increase the pressure on the onshore system, and affect the security of supply of the onshore system and the onshore electricity price. This may cause public opposition. The potential restriction and limitation of the onshore power system may motivate offshore wind. Because OEHs can supply offshore platforms, a major function may be to supply and benefit the onshore system. Onshore wind power development is slow or even opposed in some regions. OEHs may help the onshore system decarbonisation by distributing offshore wind power to shore. Another insight is that a future hydrogen market may be needed in such a model to analyse the

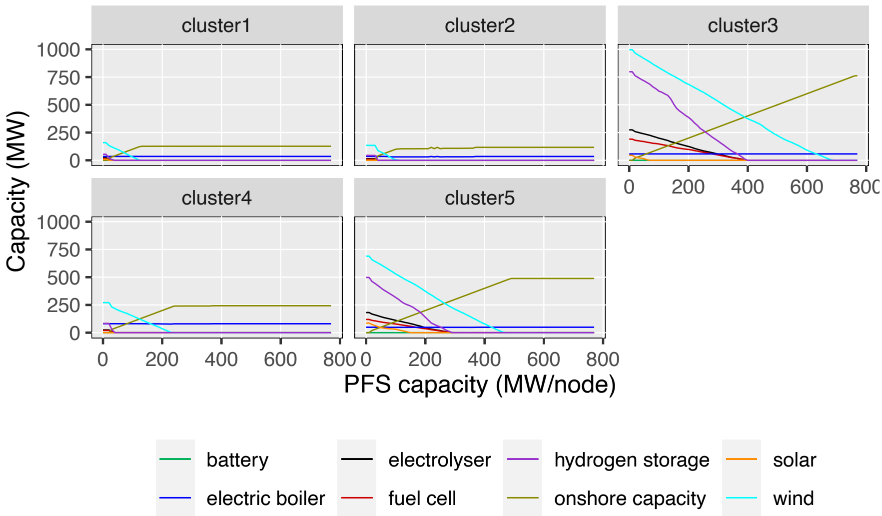

Figure I.21: Capacities of technologies in each cluster (PFS capacity sensitivity analysis, S2), hydrogen storage is measured in tonne.

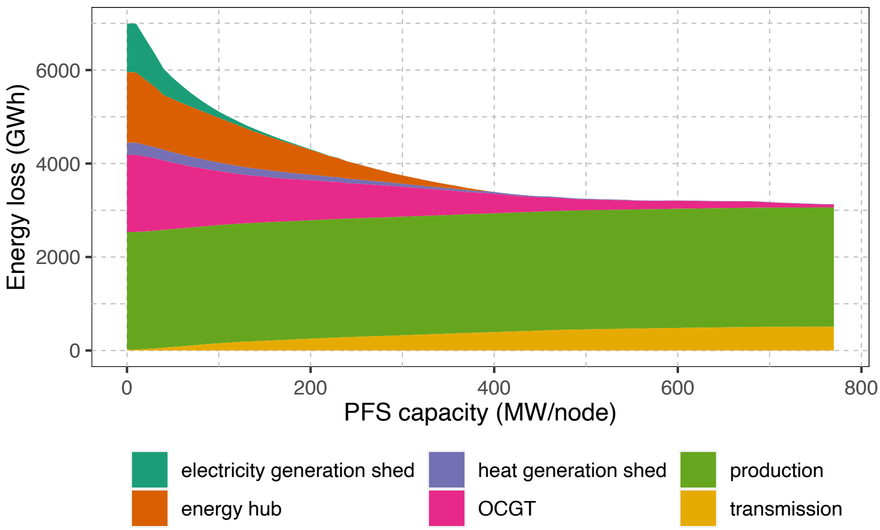

Figure I.22: Energy loss (PFS capacity sensitivity analysis, S2).

value of OEHs properly. Because the main function of OEHs is to supply offshore fields in the short- to mid-term, and serve for clean energy export in the long term. Including a hydrogen market can realise the long-term value of OEHs. The model can then be used for the techno-economical analysis of OEHs in onshore and offshore energy systems for countries with different energy policies in terms of offshore wind, onshore wind and green hydrogen.

Energy storage becomes very important in a system with higher wind power penetration. Hydrogen can be a promising option for long-term large-scale clean energy storage. Some offshore regions may have massive underground storage capacity. In such a case, the model can analyse whether OEHs with storage can be a cost-efficient solution for large-scale storage to help introduce more wind power in the system, and then help the energy transition towards zero emission.

Offshore energy system planning is of interest in many regions around the world. Decarbonising platforms may be a target during the planning in regions like the Gulf of Mexico and the Brazilian continental shelf. The model can be applied for the analysis of such locations. The model can also be used to analyse the interaction of an offshore energy system and onshore energy system transition. Regardless of the case study location, investment planning of an energy system typically aims to find optimal investment decisions that can fulfil the required energy load under some constraints. The model formulation is general, and there are no case-specific constraints. All locations and transmission lines are represented by nodes and arcs, respectively. A different configuration for each location and a cost model for each branch can be defined based on data. Model parameters, constraints, and variables can be modified according to the specific problem of the study.

Although the paper gives several insights and implications, the case study has some limitations: (a) we consider a simple network topology without considering the interconnections between fields clusters, and the interconnections may help OEHs distribute power; (b) we do not consider the capacity expansion of the onshore power system; and (c) we only consider using OEHs to decarbonise offshore fields, whereas, in reality, such hubs can provide service to more onshore and offshore industries, therefore, analysing OEHs also has relevance to onshore systems.

I.8 Conclusions and future work

This paper presents a multi-carrier offshore energy system investment planning optimisation model with a high degree of operational detail to find cost-optimal solutions for decarbonising NCS energy supply. The major novelties and contributions are: (1) formulating OEHs in an integrated MILP investment and operational model for large-scale offshore energy system planning; (2) modelling the device-level energy consumption of the offshore platforms with hourly time resolution on a large scale; and (3) conducting a large-scale analysis of the value of OEHs in the North Sea offshore energy system transition towards decarbonised energy supply. Results from our case study indicate that: (1) OEHs can reduce up to 10% of the energy loss and 49% of the emissions with CO_2 tax above 290 €/tonne; (2) OEHs can reduce energy loss by 53% in a near zero emission system; (3) a carbon budget may be necessary to enable a zero emission energy system in addition to CO_2 tax; and (4) the system cuts about 65% of the initial emissions when CO_2 tax is 55 €/tonne, and approximately 84% of the CO_2 emissions can be cut if CO_2 tax is increased to Norway's target of 200 €/tonne.

Although the deterministic MILP model in this paper has led to many insights, there are several possible extensions. A deterministic optimisation model is not capable of representing load and supply uncertainties. Therefore, we aim to develop a stochastic optimisation model (Birge & Louveaux, 2011) and incorporate long-term and short-term uncertainties in future work. In addition, multiple investment stages are needed to represent the investment planning problem more realistically. Besides, we only consider using OEHs for fields decarbonisation, which makes OEHs seem less attractive than other technologies due to their high costs. However, OEHs can have various advantages such as energy provision to offshore fish farming, maritime transport, and using the infrastructure past the lifetime of the oil and gas fields for purposes such as exporting hydrogen. These may motivate the investments in OEHs, which we aim to include some of the aspects in future. Finally, more work can be done on offshore network topology and the representation of the onshore power system.

CRediT author statement

Hongyu Zhang: Conceptualisation, Methodology, Software, Validation, Formal analysis, Investigation, Visualisation, Data curation, Writing - original draft, Writing - review & editing. **Asgeir Tomasgard:** Conceptualisation, Supervision, Writing - review & editing, Funding acquisition. **Brage Rugstad Knudsen:** Conceptualisation, Supervision, Writing - review & editing. **Harald G. Svendsen:** Conceptualisation, Writing - review & editing. **Steffen J. Bakker:** Conceptualisation, Writing - review & editing. **Ignacio E. Grossmann:** Conceptualisation, Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix I.A Nomenclature

Investment planning related sets

$\mathcal{I}$	set of operational nodes
$\mathcal{I}_0$	set of investment nodes

$\mathcal{I}_i$	set of investment nodes i ($i \in \mathcal{I}_0$) ancestor to operational node i ($i \in \mathcal{I}$)
$\mathcal{P}$	set of technologies

Operation related sets

$\mathcal{B}^E$	set of electric boilers
$\mathcal{C}$	set of compressors
$\mathcal{E}$	set of electrolysers
$\mathcal{F}$	set of fuel cells
$\mathcal{G}$	set of gas turbines
$\mathcal{L}$	set of subsea cables
$\mathcal{N}$	set of time slices
$\mathcal{P}^*$	set of all electric boilers, electrolysers and fuel cells ($\mathcal{P}^* = \mathcal{B}^E \cup \mathcal{E} \cup \mathcal{F}$)
$\mathcal{P}^U$	set of pumps
$\mathcal{R}$	set of renewable units (offshore wind and offshore solar)
$\mathcal{S}^E$	set of electricity storage
$\mathcal{S}^{Hy}$	set of hydrogen storage facilities
$\mathcal{T}$	set of hours in all time slices
$\mathcal{T}_n$	set of hours in time slice n ($n \in \mathcal{N}$)
$\mathcal{Z}$	set of all locations, including platforms $\mathcal{Z}^P$, OEHs $\mathcal{Z}^H$, and onshore buses $\mathcal{Z}^O$ ($\mathcal{Z} = \mathcal{Z}^P \cup \mathcal{Z}^H \cup \mathcal{Z}^O$)

Investment planning related parameters

κ	scaling effect depending on time step between successive investment nodes
C_{pi}^{Fix}	unitary fix operational and maintenance cost of technology p in operational node i ($p \in \mathcal{P}, i \in \mathcal{I}$) [€/MW, €/MWh, €/kg]
C_{pi}^{InvF}	fixed capacity independent investment cost of technology p in investment node i ($p \in \mathcal{P}, i \in \mathcal{I}_0$) [€]
C_{pi}^{InvV}	unitary investment cost of technology p in investment node i ($p \in \mathcal{P}, i \in \mathcal{I}_0$) [€/MW, €/MWh, €/kg]
Q_p	capacity of a unit of technology p ($p \in \mathcal{P}$) [MW, MWh, kg]
X_p^{Max}	maximum accumulated capacity of technology p ($p \in \mathcal{P}$) [MW, MWh, kg]
Y_{pi}	maximum number of newly invested units of technology p in investment node i ($p \in \mathcal{P}, i \in \mathcal{I}_0$)

Operation related parameters

α_g^G/α_f^F	maximum ramp rate of gas turbines /fuel cells ($g \in \mathcal{G}, f \in \mathcal{F}$) [MW/MW]
η^*	efficiency of compressors, electric boilers, fuel cells, gas turbines, heat recovery of gas turbines electric storage and transmission lines $* = \{$C, BE, F, G, HrG, SE, L$\}$ indexed by related sets
η^{EF}	conversion factor of electrolyser to inject hydrogen directly to fuel cell [MWh/kg]
η^{ES}	conversion factor of electrolyser to inject hydrogen to the storage facility [MWh/kg]
γ_s^{SE}	power ratio of electricity store s ($s \in \mathcal{S}^E$) [MW/MWh]
μ^E	yearly CO_2 emission limit (tonne)

ρ_f^F	hydrogen consumption factor of fuel cell f ($f \in \mathcal{F}$) [kg/MW]
σ_z^{Res}	spinning reserve factor on platform z ($z \in \mathcal{Z}^P$)
τ_{zt}^{EP}	electricity price in onshore bus z in period t ($z \in \mathcal{Z}^O, t \in \mathcal{T}$) [€/MW]
C_g^G	total operational cost of gas turbine g ($g \in \mathcal{G}$) [€/MW]
$C^{Shed,l}$	load shed penalty cost of power ($l = P$) and heat ($l = H$) [€/MW]
C_g^G	total operational cost of generating 1 MW power from gas turbine g ($g \in \mathcal{G}$) [€/MW]
E_g^G	emission factor of gas turbine g ($g \in \mathcal{G}$) [tonne/MWh]
E_g^G	emission of CO_2 of gas turbine g burning fuel ($g \in \mathcal{G}$) [t/MWh]
H_t	number of hour(s) in one operational period t
P_{zt}^{DP}	power demand on platform z period t ($z \in \mathcal{Z}, t \in \mathcal{T}$) [MW]
R_{rt}^R	capacity factor of renewable unit r in period t ($r \in \mathcal{R}, t \in \mathcal{T}$)
W_t	weighted length of one operational period t

Investment planning related variables

c^{INV}	total investment and fixed operating and maintenance costs [€]
c_i^{OPE}	total operational costs in operational node i ($i \in \mathcal{I}$)[€]
x_{pi}^{Acc}	accumulated capacity of device p in operational node i ($p \in \mathcal{P}, i \in \mathcal{I}$) [MW, MWh, kg]
x_{pi}^{Inst}	newly invested capacity of device p in investment node i_0 ($p \in \mathcal{P}, i \in \mathcal{I}_0$) [MW, MWh, kg]
y_{pi}	number of units of newly invested technology p in investment node i_0 ($p \in \mathcal{P}, i \in \mathcal{I}_0$)

Operation related variables

p_{et}^E	power consumption of electrolyser e in period t ($e \in \mathcal{E}, t \in \mathcal{T}$) [MW]
p_{ft}^F	power generation of fuel cell f in period t ($f \in \mathcal{F}, t \in \mathcal{T}$) [MW]
p_{bt}^{BE}	power consumption of electric boiler b in period t ($b \in \mathcal{B}^E, t \in \mathcal{T}$) [MW]
p_f^{AccF}	accumulated capacity of fuel cell f ($f \in \mathcal{F}, t \in \mathcal{T}$) [MW]
p_{gt}^G	power generation of gas turbine g in period t ($g \in \mathcal{G}, t \in \mathcal{T}$) [MW]
p_{gt}^{ResG}	power reserved of gas turbine g for spinning reserve requirement in period t ($g \in \mathcal{G}, t \in \mathcal{T}$) [MW]
p_g^{AccG}	accumulated capacity of gas turbine g ($g \in \mathcal{G}$) [MW]
p_{lt}^L	power flow in line l in period t ($l \in \mathcal{L}, t \in \mathcal{T}$) [MW]
p_l^{AccL}	accumulated capacity of line l ($l \in \mathcal{L}$) [MW]
p_{st}^{ResSE}	power reserved in electricity store s for spinning reserve requirement in period t ($s \in \mathcal{S}^E, t \in \mathcal{T}$) [MW]
$p_{st}^{SE+}/p_{st}^{SE-}$	charge/discharge power of electricity store s in period t ($s \in \mathcal{S}^E, t \in \mathcal{T}$) [MW]
$p_{zt}^{GShed,l}$	generation shed for power ($l = P$) and heat ($l = H$) at z in period t ($z \in \mathcal{Z}, t \in \mathcal{T}$) [MW]
p_{zt}^{PFS}	power supply from onshore bus z in period t ($z \in \mathcal{Z}^O, t \in \mathcal{T}$) [MW]
$p_{zt}^{Shed,l}$	load shed for power ($l = P$) and heat ($l = H$) at z in period t ($z \in \mathcal{Z}, t \in \mathcal{T}$) [MW]
q_{st}^{SE}	energy level of electricity store s at the start of period t ($s \in \mathcal{S}^E, t \in \mathcal{T}$) [MWh]
q_s^{AccSE}	accumulated storage capacity of electricity store s ($s \in \mathcal{S}^E$) [MWh]

$v_{st}^{SHy+}/v_{st}^{SHy-}$	injection/withdraw of hydrogen to (from) hydrogen storage s in period t ($s \in \mathcal{S}^{Hy}, t \in \mathcal{T}$) [kg]
v_{st}^{SHy}	storage level of hydrogen storage s in period t ($s \in \mathcal{S}^{Hy}, z \in \mathcal{Z}^{H}, t \in \mathcal{T}$) [kg]
v_{s}^{AccSHy}	accumulated storage capacity of hydrogen store s ($s \in \mathcal{S}^{Hy}, t \in \mathcal{T}$) [kg]

Appendix I.B Calculation of energy loss

The indices, summation and multiplication of one hour are omitted.

$$\begin{aligned} q^{Loss} =& p^{GShed} + p^{GShedH} + (\frac{1}{\eta^G} - 1 - \eta^{HrG})p^G + (1-\eta^l)p^l \\ &+ p^E - \theta^{Hy}(\frac{p^F}{\eta^F\theta^{Hy}} - v^{SHy-} + v^{SHy+}) + (\frac{1}{\eta^F} - 1)p^F, \end{aligned}$$

where $(1-\eta^l)p^l$ calculates the total energy losses of electricity storage, separators, compressors, pumps, electric boilers and transmission lines. The hydrogen energy content is denoted by θ^{Hy}.

Appendix I.C Definitions of model parameters

The total operational cost of a gas turbine is defined by

$$C_g^G = C_g^{OPEX} + \frac{C_g^{Fuel} + C^{\mathrm{CO_2}}E_g^{Fuel}}{\eta_g^G}, \tag{I.4}$$

and the emission factor of gas turbine is defined by

$$E_g^G = \frac{E_g^{Fuel}}{\eta_g^G}, \tag{I.5}$$

where C_g^{OPEX} is the variable operational cost of gas turbines. The E_g^{Fuel} is the fuel cost of gas turbines burning fuel with energy content 1 MWh. The parameter E_g^{Fuel} is the emission of CO_2 of gas turbines burning fuel with energy content 1 MWh. The efficiency of gas turbines is denoted by η_g^G.

Power demand of a platform

$$P_{zt}^{DP} = \sum_{c\in\mathcal{C}_z} \frac{V_{zt}^C ZRT}{\eta^C(\alpha-1)}\left(\gamma_c^{\frac{\alpha-1}{\alpha}} - 1\right) + \sum_{p\in\mathcal{P}_z^U} \kappa_p^{Pu}V_{pt}^{Pu}, \tag{I.6}$$

equals to the power consumption of all compressors and all pumps. The power consumption of a compressor is given by $\frac{V_{zt}^C ZRT}{\eta^C(\alpha-1)}\left(\gamma_c^{\frac{\alpha-1}{\alpha}} - 1\right)$, where V_{zt}^C is the gas compressed by a compressor, η^C is the isentropic efficiency of a compressor, α is the polytropic exponent of a compressor, γ_c is the compression ratio of a compressor, Z is compressibility factor, R is the characteristic gas constant and T is the temperature. The power consumption of a pump is given by $\kappa_p^{Pu}V_{pt}^{Pu}$, where V_{pt}^{Pu} is the fluid pumped by a pump, κ_p^{Pu} is the electricity demand as fraction of amount of fluid pumped. The detailed derivation of power consumption of compressors and pumps is presented in Svendsen (2022).

Hydrogen consumption factor of fuel cell is given by

$$\rho^F = \frac{1}{\eta_f^F \theta^{Hy}}, \tag{I.7}$$

where η_f^F is the efficiency of fuel cells and θ^{Hy} is the energy content of hydrogen.

Weighted length of a operational period is defined by

$$W_t = W_n^N H_t, \quad n \in \mathcal{N}, t \in \mathcal{T}^N, \tag{I.8}$$

where W_n^N is the weight of each slice n and H_t is the length of operational period t.

Appendix I.D Input data

Table I.2 provides an overview over the locations of the different fields.

Table I.2: Field location data

Field	Longtitude	Latitude	Cluster	Distance to center	Field	Longtitude	Latitude	Cluster	Distance to center
ALVHEIM	1.9395	59.5425	4	21.2816	OSEBERG SØR	2.9407	60.3089	4	56.0941
ATLA	2.5655	59.6521	4	26.7926	REV	1.9239	58.0205	4	55.1011
BØYLA	1.8906	59.2924	4	28.8258	RINGHORNE ØST	2.5101	59.2710	4	24.7070
BALDER	2.4079	59.2685	4	22.4603	SIGYN	2.0162	58.2760	4	27.2786
BLANE	2.4933	56.8442	2	51.1421	SINDRE	2.3471	61.2307	2	8.9022
BRAGE	3.0645	60.4766	1	36.2946	SKIRNE	2.4663	59.5995	1	18.7876
BYRDING	3.5282	61.1336	1	41.1125	SKOGUL	2.2236	59.7787	1	35.6253
EDVARD GRIEG	2.3253	58.8451	3	43.4742	SLEIPNER ØST	1.9808	58.4073	3	12.6067
EKOFISK	3.2310	56.4936	2	10.8211	SLEIPNER VEST	1.6639	58.3896	2	20.4544
ELDFISK	3.3155	56.3772	2	24.6979	SNORRE	2.0600	61.3975	2	17.8092
EMBLA	3.2736	56.2948	2	33.0210	STATFJORD	1.8027	61.1682	2	22.3646
ENOCH	1.5205	58.6309	3	26.4138	STATFJORD ØST	1.9859	61.3059	3	12.3843
FLYNDRE	2.6338	56.5497	2	34.3127	STATFJORD NORD	1.9139	61.4255	2	24.3768
FRAM	3.4836	61.0491	1	31.5435	SVALIN	2.3967	59.1362	1	36.5700
FRAM H-NORD	3.5006	61.1047	1	37.5782	SYGNA	2.0011	61.4647	1	25.9082
GIMLE	2.3458	61.2496	5	8.5919	TAMBAR	3.0129	56.9428	5	40.8781
GINA KROG	1.7013	58.5396	3	12.9160	TOR	3.3023	56.6257	3	8.0665
GJØA	3.9304	61.3045	1	68.1220	TORDIS	2.1141	61.2460	1	3.8127
GRANE	2.4377	59.1118	4	39.7075	TROLL	3.9095	60.5028	4	48.7206
GUDRUN	1.7169	58.8113	3	34.8508	TRYM	4.2407	56.3964	3	67.9529
GULLFAKS	2.1176	61.1918	5	7.3167	TUNE	2.6089	60.4144	5	54.2111
GULLFAKS SØR	2.0278	61.1654	5	12.5494	ULA	2.8675	57.0670	5	56.7312
GUNGNE	1.8885	58.3519	3	18.3356	UTGARD	1.5424	58.3444	3	29.0778
HEIMDAL	2.2214	59.5465	4	10.2065	VALE	2.2936	59.6835	4	24.9101
HOD	3.4304	56.1763	2	48.1342	VALEMON	2.2455	60.9907	2	28.9045
ISLAY	1.9251	60.5433	5	79.7225	VALHALL	3.4306	56.2307	5	42.4198
IVAR AASEN	2.1242	58.9170	3	46.1277	VEGA	3.3593	61.3396	3	61.2607
JOHAN SVERDRUP	2.6266	58.6588	3	43.9624	VESLEFRIKK	2.8778	60.7442	3	20.2442
KNARR	2.7084	61.7845	5	65.6891	VIGDIS	2.1166	61.3390	5	10.6492
KVITEBJØRN	2.4821	61.0431	5	27.8955	VILJE	2.2767	59.6433	5	20.4260
ODA	3.0430	57.0593	2	53.1470	VISUND	2.6177	61.4155	2	29.5835
OSEBERG	2.6905	60.5397	1	40.9210	VISUND SØR	2.3355	61.2720	1	8.4376
OSEBERG ØST	2.9582	60.5835	1	27.7075	VOLUND	2.0031	59.4488	1	15.6642

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Paper II

Offshore energy hubs in the decarbonisation of the Norwegian continental shelf

II

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Abstract

This paper studies the investment planning of a decarbonised Norwegian continental shelf energy system considering the connection and interfaces with the European energy system. A multi-horizon stochastic mixed-integer linear programming model is developed for such a problem. We consider short-term uncertainties, including wind and solar capacity factors, energy load, platform production profiles, and hydro power production limits. Hydrogen based energy hubs are considered both onshore and offshore for potential renewable power generation, distribution and storage. Future hydrogen market or demand is not included in the model. The results of multi-period planning towards 2050 show that: (a) offshore energy hubs are essentially wind power generation, conversion and distribution hubs, (b) a combination of offshore wind and power from shore may be a cost-efficient pathway for cutting emissions from the Norwegian continental shelf, (c) a total of 1.6 GW offshore wind may be needed to achieve a near zero emission Norwegian continental shelf energy system, 80% of which may be added in the first investment period and (d) offshore grid design is important for decarbonisation by distributing wind power efficiently; all five offshore platform clusters are connected to at least three other clusters by 2040, and they are fully connected by 2050.

Keywords: Multi-horizon stochastic programming, Mixed-integer linear programming, Offshore oil and gas decarbonisation, Investment planning under uncertainty

II.1 Introduction

Norway sets to reduce greenhouse gas emissions by at least 50-55% by 2030 compared to 1990 levels to contribute to the EU's climate target, and the Paris Agreement (Ministry of Climate and Environment, 2021). In 2020, offshore oil and gas extraction in the Norwegian Continental Shelf (NCS) produced 13.2 Mt CO_2 equivalent, which made up 26.8% of the total Norwegian greenhouse gases emissions (Statistics Norway, 2021). The oil and gas industry has the highest emissions than any other industries in Norway. Therefore, decarbonising offshore oil and gas production is crucial to meet Norway's climate goal.

Energy provision of offshore platforms was responsible for nearly 85% of the total emissions in the NCS (The Norwegian Petroleum Directorate, 2021). Nowadays, platform located gas turbines with low efficiency provide the most energy. Thus, replacing gas turbines with zero emission energy generation will cut offshore emissions. Power from shore is considered a feasible solution of clean energy provision due to the near zero emission power generation in the onshore energy system (The Norwegian Petroleum Directorate, 2020; Nguyen et al., 2016). Offshore wind is an alternative that draws more attention (Korpås et al., 2012; Svendsen et al., 2011; Equinor, 2021). However, intermittent renewable energies cannot fulfil the security of supply requirements of the platforms. Energy storage may be needed to fully replace gas turbines. The space and weight limitations of platforms may make local energy storage infeasible. An offshore energy hub was proposed in Zhang et al. (2021) to support efficient wind power generation and distribution. In Zhang et al. (2021), a deterministic Mixed-Integer Linear Programming (MILP) model was developed for the investment planning towards a zero emission NCS energy system. However, there are some limitations in the analysis in Zhang et al. (2021): (a) uncertainty is not considered in the model, (b) the onshore energy system expansion is not considered but analysed via sensitivity analysis, and (c) platforms are in isolated mode, and no interconnection among platforms is considered.

In this paper, we extend the deterministic MILP model in Zhang et al. (2021), including: (a) adding operational uncertainties in wind and solar capacity factors, energy load, platform production profiles, and hydro power production profile, (b) considering onshore power system expansion, (c) exploring different network topology, and (d) making multi-period investment planning towards 2050.

The outline of the paper is as follows: Section II.2 gives the background knowledge of stochastic programming and energy hub modelling. Section II.3 introduces the problem and modelling strategies. Section II.4 presents the multi-horizon stochastic MILP model. Section II.5 presents the preliminary results. Section II.6 concludes the paper and suggests further research.

II.2 Literature review

This paper uses stochastic programming to solve an investment planning problem for a decarbonised NCS energy system. Offshore energy hubs is an offshore investment option in addition to offshore wind, offshore solar, subsea cables, battery and electric boiler. In the following, we present background knowledge of stochastic programming and energy hubs modelling.

II.2.1 Stochastic programming

Considering operational uncertainty while conducting long-term investment planning is important for an energy system with higher penetration of renewable energies.

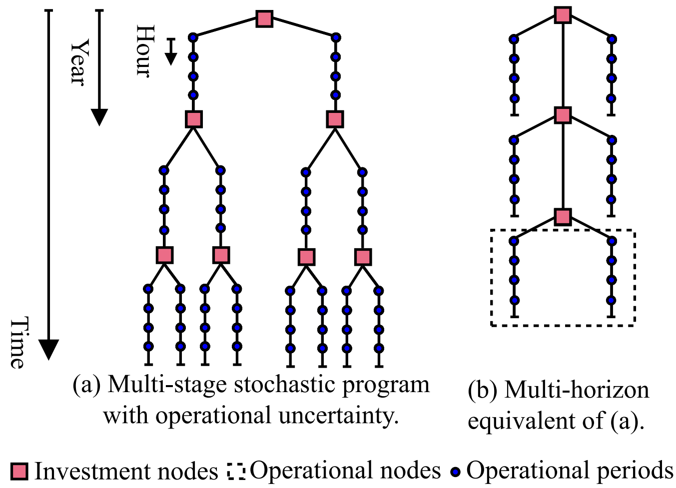

Figure II.1: Illustration of scenario trees of multistage stochastic programming and its multi-horizon counterpart (with operational uncertainty), adapted from Kaut et al. (2014) and Skar et al. (2016).

The electricity system in regulated markets is the best developed area for the use of stochastic programming in energy (Wallace & Fleten, 2003). Stochastic programming is widely used in power system (Backe et al., 2022; Lara et al., 2019; Philpott et al., 2016; Jin et al., 2011; van der Weijde & Hobbs, 2010), natural gas system (Fodstad et al., 2016), offshore oil and gas infrastructure planning (Gupta & Grossmann, 2014), hydrogen network (Galan et al., 2019), among others.

Using traditional stochastic programming in an investment planning problem may result in a large scenario tree. A multi-horizon formulation was proposed in Kaut et al. (2014) that reduces the problem sizes drastically. The scenario tree reduces in size by embedding operational nodes into their respective strategic nodes, see Figure II.1 for a comparison between traditional multi-stage stochastic programming scenario tree and multi-horizon programming scenario tree. There are two conditions for applying multi-horizon stochastic programming, (1) strategic uncertainty is independent of the operational uncertainty, and (2) the last operational decision in a strategic node has no impact on the first operational decision in the following strategic node (Kaut et al., 2014). This approach is widely used in energy system planning, see Wu et al. (2017); Turgut et al. (2021); Zhang et al. (2021); Backe et al. (2022). This paper uses the multi-horizon approach to model a multi-period investment planning problem with short-term uncertainties. We define the entire operational problem succeeding an investment node as an operational node. There are some scenarios generated from certain scenario generation routines for each operational node, and each scenario has some operational periods. We do not consider multi-stage operational trees in the operational node. Therefore, such a problem is a two-stage stochastic programming.

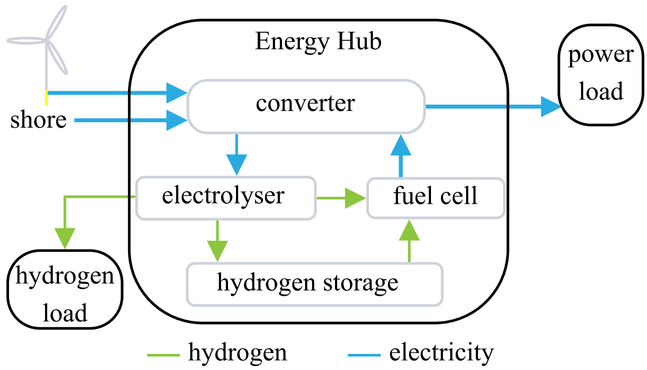

Figure II.2: Illustration of an energy hub, adapted from Zhang et al. (2021).

II.2.2 Offshore energy hubs modelling

An energy hub is a physical connection point with energy storage where multiple energy carriers can be converted, conditioned, and stored (Geidl et al., 2007). Conversion means converting energy in one form to another, such as converting electricity to hydrogen. Conditioning means to change the operating parameter of energy carriers, e.g., change voltage of electricity. The energy can then store in a storage unit of energy hubs. Energy hubs may have quite different components depending on their functions. We refer the reader to Mohammadi et al. (2017) for a comprehensive review of applications and models of energy hubs. The previous work using the energy hub concept mainly focus on the onshore energy system integration. More specifically, sector coupling of electricity, natural gas and heat. In real life, the energy hub concept is broadened, such as Danish Energy Agency (2021) and North Sea Wind Power Hub Programme (2021) where the hubs can be simply a wind power generation and distribution hub. The offshore energy hubs are mainly planned to use offshore wind power as energy input and convert and distribute wind power. However, as more offshore wind is available (European Commission, 2020), offshore energy hubs can also convert surplus wind power, for example, to hydrogen for clean energy export or energy storage. We consider energy hubs both in onshore and offshore energy systems. This paper considers energy hubs with converter, electrolysers, fuel cells, and hydrogen storage facilities. The hubs produce green hydrogen from surplus wind power and store it. Furthermore, energy hubs can be deployed both onshore and offshore. An illustration of the energy hubs considered in this paper is presented in Figure II.2.

II.3 Problem description and modelling strategies

This section first introduces the proposed NCS energy system planning problem. Then we present the temporal and spatial representation of such a problem. Finally, we give the modelling assumptions.

The problem aims to make optimal investment decisions for a set of offshore and onshore technologies. Although the focus is on the NCS energy system, including

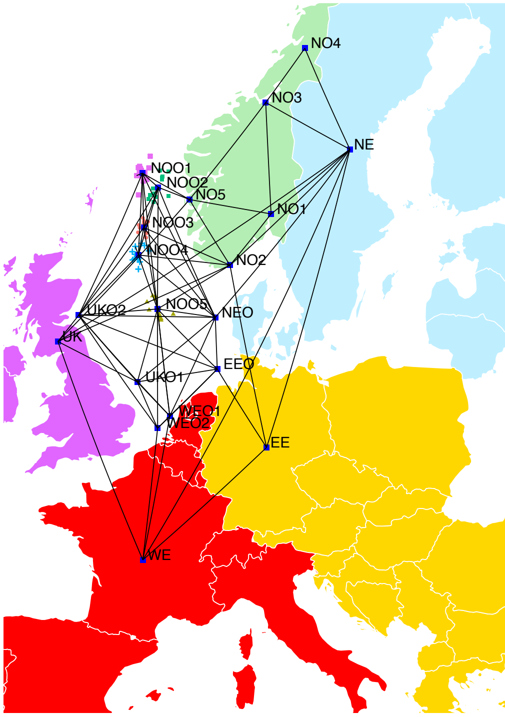

Figure II.3: The North Sea grid (NOX represent Norwegian onshore nodes and NOOX represent Norwegian offshore nodes.

onshore system expansion is important. The onshore load still needs to be fulfilled after part of the generation is distributed offshore. The offshore technologies include: (a) platform located devices (electric boiler, battery), (b) offshore renewables (offshore wind and offshore solar), (c) offshore energy hubs (converters, electrolysers, fuel cells, and hydrogen storage facilities) and subsea cables (HVAC and HVDC). The onshore technologies include: (a) 22 kinds of generators, (b) onshore energy hubs, (c) energy storage (hydro pump storage and battery) and (d) overhead HVAC and HVDC cables. The development of capital expenditures, fixed operational costs are assumed to be known.

The problem is a cost minimisation problem, including investment and operational costs aiming to determine: (a) the optimal capacities of technologies and (b) optimal operational scheduling of generators, storage and approximate power flow among regions under stochastic operational scenarios.

II.3.1 Temporal representation

The investment planning problem can span over a few decades, whereas the operational problem is optimised with an hourly time horizon using representative hours. Combining strategic and operational time horizons in the same model and including short-term uncertainty can make the problem intractable. Therefore, we choose to make investment planning every κ year in the strategic time horizon instead of yearly.

In the operational time horizon, we choose S representative slices from the sample space and scale them up to represent a whole operational year. We also assume the operational status will not change between two successive investment nodes and scale the expected operational cost up by κ times to represent the total operational costs of an operational node.

II.3.2 Spatial representation

We include detailed modelling of the NCS and keep a part of the information of the European onshore system. The European countries are aggregated into representative nodes and connected by representative transmission lines to keep such a problem reasonable size. The platforms on the NCS are clustered and aggregated into some representative platforms (Zhang et al., 2021). The resulted network topology is presented in Figure II.3.

II.3.3 Modelling assumption

We assume a κ years investment delay meaning that the investment made at one investment node start affecting the system operation from the following investment nodes onwards. For simplicity, we assume the pressure levels and temperatures to take typical values on the North Sea, leading to a linear formulation. Kirchhoff voltage law is omitted, and the model is an energy flow model. We assume no mass loss during production. We assume linear costs models for transnational transmission lines and onshore technologies due to their large size and aggregated representation. The linear costs model also applies for offshore wind and solar because of the potentially large size and the flexibility of their unit size. However, step-wise cost models are assumed for offshore energy hubs and transmission lines in the NCS.

II.4 Mathematical model

II.4.1 Objective function

$$\min f(\mathbf{x}) + \kappa \sum_{i \in \mathcal{I}} \delta_i^I \pi_i g(x_i, c_i) \tag{II.1}$$

The objective function Equation (II.1) is to minimise the total investment ($f(\mathbf{x})$) and the expected operational ($\kappa \sum_{i \in \mathcal{I}} g(x_i, c_i)$) costs over the planning horizon. The expected operational cost $g(x_i, c_i)$ is described in Section II.4.3, where x_i and c_i are vectors containing capacities and costs information respectively.

II.4.2 Investment planning constraints

Equation (II.2a) calculates the expected total discounted capacity dependent investment costs, fixed operating and maintenance costs and fixed capacity independent investment costs. For each investment node, the investment costs parameters are adjusted if the lifetimes of technologies exceed the remaining planning horizon to account for salvage value. We define $\mathbf{x}$ to be a vector collecting available capacities of all technologies ($\mathcal{P}$) and lines ($\mathcal{L}$) for all operational nodes ($\mathcal{I}$). Constraints (II.2b) and (II.2c) represent that the available capacity of a technology (x^{PAcc}_{pzi}) or a line (x^{LAcc}_{li}) at an operational node equals to its historical capacity (X^{PHist}_{pz} or X^{LHist}_{l}) and the sum of newly invested capacities (x^{PInst}_{pzi} or x^{LInst}_{li}) in its ancestor investment nodes ($\mathcal{I}_i$) that are not retired. A binary variable γ^{P}_{pzi} decides whether technology $p \in \mathcal{P}$, in location $z \in \mathcal{Z}$ is built investment period $i \in \mathcal{I}_0$. A binary variable γ^{L}_{li} indicates whether line $l \in \mathcal{L}$ is built in investment period $i \in \mathcal{I}_0$. Constraint (II.2d) and (II.2e) restrict the maximum capacity that can be invested in an investment node. Constraint (II.2d) and (II.2e) state the maximum installed capacity in an operation node.

$$
\begin{aligned}
f(\mathbf{x}) = \sum_{i\in\mathcal{I}_0} \delta_i^{I_0}\pi_i^{I_0} \Bigg(& \sum_{p\in\mathcal{P}}\sum_{z\in\mathcal{Z}} (C^{PInv}_{pi} x^{PInst}_{pzi} + C^{PFInv}_{pi}\gamma^{P}_{pzi}) + \\
& \sum_{l\in\mathcal{L}} (C^{LInv}_{li} x^{LInst}_{li} + C^{LFinv}_{li}\gamma^{L}_{li}) \Bigg) + \\
& \kappa\delta_i^{I}\pi_i^{I} \sum_{i\in\mathcal{I}} \left(\sum_{p\in\mathcal{P}}\sum_{z\in\mathcal{Z}} C^{PFix}_{pi} x^{PAcc}_{pzi} + \sum_{l\in\mathcal{L}} C^{LFix}_{li} x^{LAcc}_{li} \right) && \text{(II.2a)}
\end{aligned}
$$

$$
\begin{aligned}
& x^{PAcc}_{pzi} = X^{PHist}_{pz} + \sum_{i_0\in\mathcal{I}_i|\kappa(i-i_0)\le H_p} x^{PInst}_{pzi}, && p\in\mathcal{P}, z\in\mathcal{Z}, i\in\mathcal{I} && \text{(II.2b)}\\
& x^{LAcc}_{li} = X^{LHist}_{l} + \sum_{i_0\in\mathcal{I}_i|\kappa(i-i_0)\le H_l} x^{LInst}_{li}, && l\in\mathcal{L}, i\in\mathcal{I} && \text{(II.2c)}\\
& 0 \le x^{PInst}_{pzi} \le X^{PMaxb}_{pzi}\gamma^{P}_{pzi}, && p\in\mathcal{P}, z\in\mathcal{Z}, i\in\mathcal{I}_0 && \text{(II.2d)}\\
& 0 \le x^{LInst}_{li} \le X^{LMaxb}_{li}\gamma^{L}_{lzi}, && l\in\mathcal{L}, i\in\mathcal{I}_0 && \text{(II.2e)}\\
& 0 \le x^{PAcc}_{pzi} \le X^{PMax}_{pz}, && p\in\mathcal{P}, z\in\mathcal{Z}, i\in\mathcal{I} && \text{(II.2f)}\\
& 0 \le x^{LAcc}_{li} \le X^{LMax}_{l}, && l\in\mathcal{L}, i\in\mathcal{I} && \text{(II.2g)}\\
& \gamma^{P}_{pzi}, \gamma^{L}_{li} \in \{0,1\}, && && \text{(II.2h)}\\
& x^{PInst}_{pzi}, x^{LInst}_{li}, x^{PAcc}_{pzi}, x^{LAcc}_{li} \in \mathbb{R}^{+}_{0}. && && \text{(II.2i)}
\end{aligned}
$$

II.4.3 Operational constraints

The operational cost function $g(x, c)$, which is included in the objective function Equation (II.1) for each operational node i, is described by Equation (II.3a) that includes total operating costs of all devices and energy load shedding costs. Equation (II.3a) calculates the expected operational costs over scenarios Ω. All variables are indexed by operational node i and scenario ω, and we omit them for ease of notation. Vectors x and c contain capacities and costs information, respectively. Constraints (II.3b) and (II.3c) ensure devices (y^{P}_{pzt}) and transmission lines (y^{L}_{lt}) are within their capacities ($x^{PAcc}_{pz}, x^{LAcc}_{l}$). Constraint (II.3d) gives the energy balance at each region, where y^{G}_{gt}, y^{F}_{fzt} and y^{R}_{rzt} are power generation of generators, fuel cells and renewables respectively. Moreover, we define y^{E}_{ezt} to be the power that goes into electrolysers and l^S_{szt}, y^{S+}_{szt} and y^{S-}_{szt} represent the storage level, input and output energy of storage facilities. The energy demand Y^D_{zt} can be modelled corresponding to the specific sector, such as offshore platforms. The modelling of offshore platforms is described in details in Zhang et al. (2021). Constraint (II.3e) states the storage balance of electricity storage facilities. Constraint (II.3g) states the storage balance of hydrogen storage facilities. Constraint (II.3g) gives the hydrogen nodal balance of offshore energy hubs, where v^{SHy-}_{szt} and v^{SHy+}_{szt} are the hydrogen output and input of hydrogen storage facilities. Constraint (II.3h) restricts the total emissions. The complete stochastic MILP problem consists of Equations (II.1)-(II.3).

$$g(x,c) = \sum_{\omega \in \Omega} \pi^{\Omega}_{\omega} \sum_{s \in \mathcal{S}^T} \sum_{t \in \mathcal{T}} \sum_{z \in \mathcal{Z}} W_s \left(\sum_{p \in \mathcal{P}} C^P_p y^P_{pzt} + C^{Shed} y^{LShed}_{zt} \right) \tag{II.3a}$$

$$0 \leq y^P_{pzt} \leq x^{PAcc}_{pz}, \qquad p \in \mathcal{P}, z \in \mathcal{Z}, t \in \mathcal{T} \tag{II.3b}$$

$$-x^{LAcc}_l \leq y^L_{lt} \leq x^{LAcc}_l, \qquad l \in \mathcal{L}, t \in \mathcal{T} \tag{II.3c}$$

$$\begin{aligned}&\sum_{g \in \mathcal{G}} y^G_{gt} + \sum_{l \in \mathcal{L}} A_{zl} y^L_{lt} + \sum_{f \in \mathcal{F}} y^F_{fzt} + y^{LShed}_{zt} + \sum_{r \in \mathcal{R}} y^R_{rzt} = \\ &Y^D_{zt} + \sum_{s \in \mathcal{S}} (y^{S+}_{szt} - y^{S-}_{szt}) + \sum_{e \in \mathcal{E}} y^E_{ezt}, \qquad z \in \mathcal{Z}, t \in \mathcal{T}\end{aligned} \tag{II.3d}$$

$$l^S_{sz(t+1)} - l^S_{szt} = \eta^S_s y^{S+}_{szt} - y^{S-}_{szt}, \qquad s \in \mathcal{S}, z \in \mathcal{Z}, t \in \mathcal{T} \tag{II.3e}$$

$$l^{SHy}_{sz(t+1)} - l^{SHy}_{szt} = v^{SHy+}_{szt} - v^{SHy-}_{szt}, \qquad s \in \mathcal{S}^{Hy}, z \in \mathcal{Z}, t \in \mathcal{T} \tag{II.3f}$$

$$\begin{aligned}&\sum_{e \in \mathcal{E}} y^E_{ezt} + \sum_{s \in \mathcal{S}^{Hy}} \eta^{EF} v^{SHy-}_{szt} = \\ &\sum_{s \in \mathcal{S}^{Hy}} \eta^{ES} v^{SHy+}_{szt} + \sum_{f \in \mathcal{F}} \eta^{EF} y^F_{fzt}, \qquad z \in \mathcal{Z}, t \in \mathcal{T}\end{aligned} \tag{II.3g}$$

$$\sum_{s \in \mathcal{S}^T} \sum_{z \in \mathcal{Z}} \sum_{t \in \mathcal{T}} \sum_{g \in \mathcal{G}} \frac{W_s \rho^G_g y^G_{gzt}}{\eta^G_g} \leq E^{\mathrm{CO_2}}, \tag{II.3h}$$

$$y^L_{lt} \in \mathbb{R}_0, \tag{II.3i}$$

$$\begin{aligned}&y^P_{pz}, y^G_{gzt}, y^F_{fzt}, y^{LShed}_{zt}, y^R_{rzt}, y^{S+}_{szt}, y^{S-}_{szt}, y^E_{ezt}, \\ &l^S_{szt}, l^{SHy}_{szt}, v^{SHy-}_{szt}, v^{SHy+}_{szt}, x^{PAcc}_{pz}, x^{LAcc}_l \in \mathbb{R}^+_0.\end{aligned} \tag{II.3j}$$

II.5 Results

We demonstrate the results of the multi-period investment planning and operational problem given by Equations (II.1)-(II.3) towards 2050. The problem consists of 1,072,525 continuous variables, 186 binary variables and 12,843,006 constraints. We implemented the model in Julia 1.7.1 using JuMP (Dunning et al., 2017) and solved it with Gurobi 9.5.0 (Gurobi Optimization, LLC, 2021) on a computer cluster with a 2x 3.6GHz 8 core Intel Xeon Gold 6244 CPU and 384 GB of RAM, running on CentOS Linux 7.9.2009.

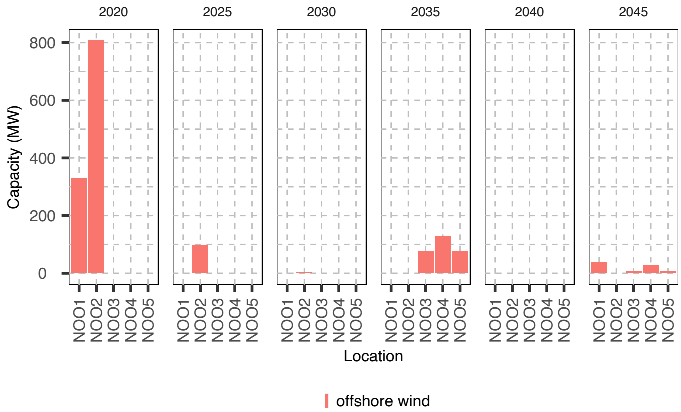

Figure II.4: Investment of offshore energy hubs.

Table II.1: Yearly emissions in each offshore fields cluster (Zhang et al., 2021).

	NOO1	NOO2	NOO3	NOO4	NOO5
Emission (Mt)	1.72	2.46	0.40	0.62	0.30

II.5.1 Case study

The case study is carried out on the European energy system with detailed modelling of the NCS. After applying the aggregation strategy described in Section II.3.2, the system is represented by 25 regions and 73 candidate transmission lines. In each operational node, we generate three scenarios. In each scenario, we randomly select one day with hourly resolution from four seasons and scale them up to represent a whole operational year. Onshore system data, including costs, historical capacities of technologies and time-series data, are collected and aggregated from Backe et al. (2021). The costs and historical capacities of technologies are presented in II.A. Platform production and hydrogen system data are included in Zhang et al. (2021). The full model given by Equations (II.1)-(II.3) takes approximately 5.4 hours to solve.

II.5.1.1 Offshore energy hubs

The invested capacities in offshore energy hubs are shown in Figure II.4. From Table II.1, we can see that offshore regions NOO2 and NOO1 have the highest emissions among platform clusters on the NCS. We only consider the emissions from the gas turbines that are used for the energy provision of platforms. The model decides to invest in approximately 800 MW and 300 MW offshore wind around NOO2 and NOO1, respectively. In addition, from Figure II.7, we can see that the investments in cables connecting these two regions and cables for taking power from onshore node NO5. Therefore, a combination of offshore wind and power from shore is needed for decarbonisation. Moreover, transmission is needed for compensating for the wind variation in those regions. An extra 100 MW offshore wind is added to region NOO2 in 2025. In 2030, nearly no investments are made in the offshore energy hubs.

Figure II.5: Invested capacity of platform located technologies. No investment are made in battery and gas turbine.

However, a cable connecting NO2 and NOO3 is invested in decarbonising NOO3. In 2035, offshore wind is invested in the rest NCS nodes to cope with the emissions target in 2040. From 2035 to 2040, we see a significant increase in cables connecting the Norwegian offshore regions. Each region are connected with an onshore system and surrounded by offshore wind farms in 2040. Because no hydrogen market or demand is considered in the model, no investments are made in hydrogen-related technologies. This suggests that a hydrogen system is costly if it is only used as energy storage. Connecting the regions with cables is a cheaper alternative for compensating renewable volatility.

II.5.1.2 Platform located technologies

Figure II.5 shows the investments in platform located devices. As gas turbines are replaced by clean power, heat recovery of gas turbines are not enough to meet the heat load of the separation process. Therefore, electric boilers are needed. The major investments in electric boilers take place in 2030 in all NCS regions.

II.5.1.3 Emissions

The relative changes in emissions in the EU and the NCS are presented in Figure II.6. The reference initial emissions in 2020 are 5.51 Mt/yr (Zhang et al., 2021) and 1,100 Mt/yr (Skar et al., 2016) for the NCS and the Europe respectively. All regions are governed by one emission constraint. EU emissions show the European emissions reduction relative to the initial total European emissions. Furthermore, NCS emissions show the emissions reduction of the NCS relative to initial NCS emissions. We can see that the NCS relative emissions decrease faster than Europe in 2025 and 2030. This result shows that almost half of the NCS emissions can be cut by 2030, aligning with stated climate goals. However, after 2030 the relative emission of Europe reduces faster than that of NCS. This may suggest that the first half of the NCS emission is cheaper to cut than the first half of the EU emissions. However,

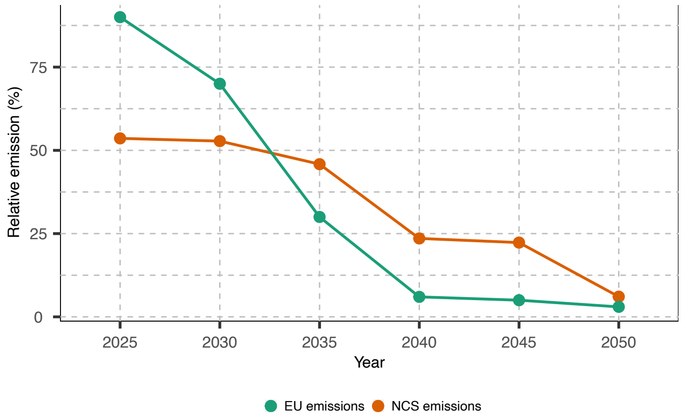

Figure II.6: Emissions of the NCS and the European energy systems.

achieving zero emission in the NCS offshore energy system is more expensive than in the European onshore system in terms of costs per CO_2 reduced. Because of that, the model chooses to cut more emissions from the European onshore system to align with the predefined emission target in the later planning horizon. We also notice that the emissions target binds nearly all the time, and no extra emissions are cut.

II.5.1.4 NCS offshore grid connection

From Figure II.7, we can see a possible development of an NCS grid towards zero emission. Until 2035, the offshore platform clusters mainly operate in isolation except for one connection between NOO1 and NOO2. However, starting from 2040, each platform cluster is connected to at least three other clusters. This may suggest that offshore grid design is essential for decarbonising the system towards zero emission. In 2050, the five platform clusters are fully connected. In addition, we notice that NOO4 and NOO5 are also connected with other offshore regions such as NEO and WEO. We do not include analysis of those connections due to the scope of the paper. Note that hydrogen storage is not seen in this case because no hydrogen load or hydrogen market is included. The platform clusters may be less connected when hydrogen storage is locally deployed to balance out the wind variation.

II.6 Summary and future work

This paper has presented a multi-horizon stochastic MILP model for the multi-period investment planning of a decarbonised NCS energy system. Operational uncertainties, including wind and solar capacity factors, oil and gas platforms production, onshore power load and hydro power production limits, were considered. Future hydrogen market or demand is not considered. We used the multi-horizon approach to reduce the problem size. The main conclusions are: (a) offshore energy hubs are essentially wind power generation, conversion and distribution hubs, (b) a combination of offshore wind and power from shore may be a cost efficient way for the decarbonisation of the NCS energy system, and a total of 1.6 GW offshore wind

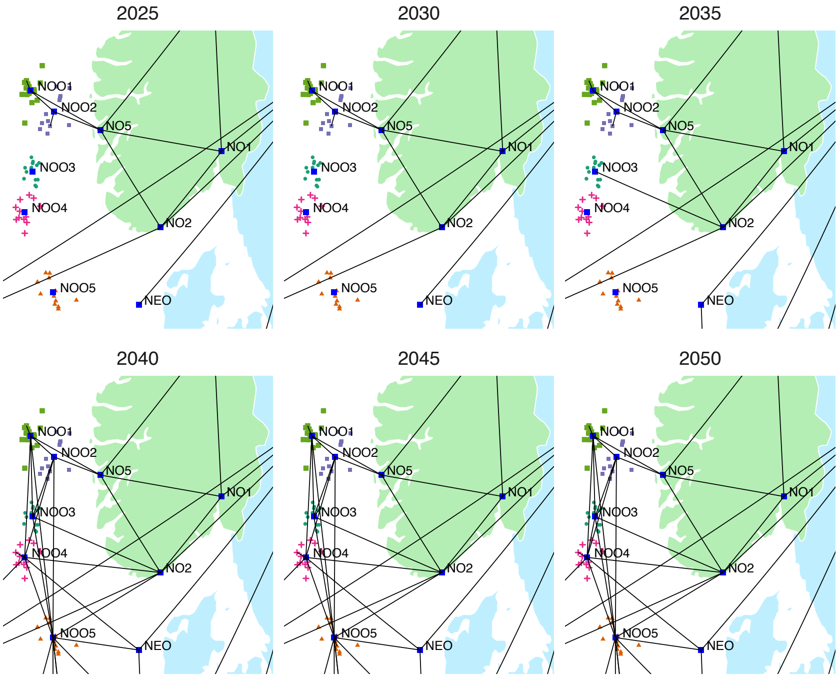

Figure II.7: The NCS gird design towards 2050.

may be deployed in the NCS for a near zero emission system, (c) offshore grid design is crucial for offshore decarbonisation by distributing wind power efficiently; 2040 may be a turning point that large-scale interconnections among platform clusters become necessary and the platform clusters may be fully connected by 2050, and (d) the emissions reduce faster in the NCS energy system than in the European power system in the first planning stages but opposite in the later stages; by 2050, 94% and 97% emissions are cut in the NCS energy system and the European power system compared with their emissions in 2020.

Although the current model with short-term uncertainty can help make investment decisions that can better cope with short-term system variation, long-term uncertainty affects investment planning. Therefore, in future studies, we aim to consider long-term uncertainty such as CO_2 tax and CO_2 budget. Additionally, we noticed the large computational burden when solving the planning problem using a commercial solver. Including long-term uncertainty will make such a problem essentially a multi-stage stochastic MILP that can be intractable. Therefore, applying decomposition schemes may be necessary to solve such planning models incorporating both long-term and short-term uncertainty.

Acknowledgements

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Appendix II.A Historical capacities and costs of technologies

Table II.2: CapEx, VarOM and FixOM of technologies (Backe et al., 2021).

Technology	CapEx (MEUR/GW, MEUR/GW/km for transmission lines)						VarOM (€/MWh)	FixOM (€/MW)
	2020	2025	2030	2035	2040	2045		
Lignite	1800.00	1800.00	1800.00	1800.00	1800.00	1800.00	3.00	5% of CapEx
Lignite CCS adv	2600.00	2600.00	2530.00	2470.00	2400.00	2330.00	3.28	
Lignite CCS sup	3799.23	3799.23	3799.23	3799.23	3799.23	3799.23	1.18	
Coal	1600.00	1600.00	1600.00	1600.00	1600.00	1600.00	2.40	
Coal CCS adv	2500.00	2500.00	2430.00	2370.00	2300.00	2230.00	2.46	
Coal CCS	3550.00	3550.00	3350.00	3350.00	3250.00	3250.00	7.30	
Gas OCGT	400.00	400.00	400.00	400.00	400.00	400.00	2.31	
Gas CCGT	720.00	720.00	690.00	690.00	660.00	660.00	2.31	
Gas CCS adv	1350.00	1350.00	1330.00	1310.00	1290.00	1270.00	1.85	
Gas CCS	1750.00	1750.00	1625.00	1625.00	1500.00	1500.00	2.90	
Oil	320.00	320.00	320.00	320.00	320.00	320.00	2.76	
Bio 10 cofiring	1600.00	1600.00	1600.00	1600.00	1600.00	1600.00	0.48	
Bio 10 cofiring CCS	2600.00	2600.00	2530.00	2470.00	2400.00	2330.00	3.28	
Nuclear	6000.00	6000.00	6000.00	6000.00	6000.00	6000.00	7.50	
Wave	6100.00	6100.00	3100.00	3100.00	2025.00	2025.00	0.10	
Geo	4970.00	4970.00	4586.00	4586.00	3749.00	3749.00	0.32	
Hydro regulated	3000.00	3000.00	3000.00	3000.00	3000.00	3000.00	0.32	
Hydro run-of-the-river	2450.00	2450.00	2400.00	2400.00	2350.00	2350.00	0.00	
Bio	2000.00	2000.00	1800.00	1800.00	1700.00	1700.00	3.56	
Wind onshore	1295.00	1295.00	1161.00	1161.00	1010.00	1010.00	0.18	
Solar	710.00	710.00	663.00	663.00	519.00	519.00	0.00	
Waste	2030.00	2030.00	2013.00	2013.00	2005.00	2005.00	0.82	
HVAC	0.66	0.66	0.60	0.60	0.60	0.60	0.00	
HVDC	2.77	2.77	2.16	2.16	1.55	1.55	0.00	

Table II.3: Fuel costs of technologies (Backe et al., 2021).

Technology	Fuel cost (€/MWh)					
	2025	2030	2035	2040	2045	2050
Lignite	5.04	5.04	5.40	5.40	5.40	5.40
Lignite CCS adv	5.04	5.04	5.40	5.40	5.40	5.40
Lignite CCS sup	5.04	5.04	5.40	5.40	5.40	5.40
Coal	8.59	10.26	12.31	13.04	13.59	14.08
Coal CCS adv	8.59	10.26	12.31	13.04	13.59	14.08
Coal CCS	8.59	10.26	12.31	13.04	13.59	14.08
Gas OCGT	28.96	31.34	34.08	36.40	37.62	38.39
Gas CCGT	28.96	31.34	34.08	36.40	37.62	38.39
Gas CCS adv	28.96	31.34	34.08	36.40	37.62	38.39
Gas CCS	28.96	31.34	34.08	36.40	37.62	38.39
Oil	45.00	51.12	56.16	58.68	62.28	63.72
Bio 10 cofiring	10.69	12.49	14.67	15.68	16.57	17.44
Bio 10 cofiring CCS	10.69	12.49	14.67	15.68	16.57	17.44
Nuclear	3.75	3.82	3.90	3.97	4.05	4.14
Bio	29.62	32.58	35.84	39.43	43.37	47.70

Table II.4: Aggregated historical capacities of technologies (Backe et al., 2021).

Technology	Historical capacity (MW)								
	NO1	NO2	NO3	NO4	NO5	NE	EE	WE	UK
Lignite	0.00	0.00	0.00	0.00	0.00	1229.00	61317.00	1124.00	228.00
Coal	0.00	0.00	0.00	0.00	0.00	7772.00	5554.00	27126.00	11715.00
Gas OCGT	35.23	89.43	4.65	48.78	56.91	3239.50	27383.50	61355.00	17195.50
Gas CCGT	35.23	89.43	4.65	48.78	56.91	3239.50	27383.50	61355.00	17195.50
Oil	0.00	0.00	0.00	0.00	0.00	7298.00	6165.00	15693.00	1798.00
Nuclear	0.00	0.00	0.00	0.00	0.00	11399.00	21341.00	79985.00	916.00
Wave	0.00	0.00	0.00	0.00	0.00	0.00	0.00	24.00	0.00
Geo	0.00	0.00	0.00	0.00	0.00	0.00	43.00	962.00	0.00
Hydro regulated	33.50	8377.50	387.75	4569.30	533.85	1663.00	17995.00	2516.00	86.00
Hydro run-of-the-river	754.13	1914.33	87.15	144.18	1218.21	4848.00	1877.00	42898.00	121.00
Bio	7.80	19.80	9.00	1.80	12.60	7531.00	11629.00	8842.00	2524.00
Wind onshore	227.37	577.17	262.35	314.82	367.29	14592.00	67628.00	59983.00	16684.00
Solar	5.85	14.85	6.75	8.10	9.45	1617.00	53534.00	43228.00	13322.00
Waste	0.00	0.00	0.00	0.00	0.00	966.00	1996.00	349.00	85.00

Table II.5: Aggregated historical capacities of transmission lines (Backe et al., 2021).

From	To	Historical capacity (MW)
NO2	NE	1640.00
NO2	UK	1400.00
NO2	NO1	2000.00
NO3	NO1	100.00
NO4	NO3	350.00
NO5	NO1	1600.00
NO5	NO2	300.00
NO5	NO3	160.00
NE	EE	2450.00
NE	NO1	1200.00
NE	NO3	650.00
NE	NO4	600.00
EE	WE	12513.00
WE	UK	3000.00
UK	NE	1400.00
NEO	NE	1120.00
EEO	EE	7166.00
WEO1	WE	357.00
WEO2	WE	3739.30
UKO1	UK	1218.00
UKO2	UK	93.20

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Paper III

A stabilised Benders decomposition with adaptive oracles for large-scale stochastic programming with short-term and long-term uncertainty

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Submitted to an international, peer reviewed journal

III

Abstract

This paper is submitted for publication and is therefore not included.

Paper IV

Integrated investment, retrofit and abandonment planning of energy systems with short-term and long-term uncertainty using enhanced Benders decomposition

Hongyu Zhang, Ignacio E. Grossmann, Brage Rugstad Knudsen, Ken McKinnon, Rodrigo Garcia Nava, Asgeir Tomasgard

Submitted to an international, peer reviewed journal

IV

This paper is submitted for publication and is therefore not included.

Paper V

Decomposition methods for multi-horizon stochastic programming

Hongyu Zhang, Èric Mor Domènech, Ignacio E. Grossmann, Asgeir Tomasgard

Submitted to an international, peer reviewed journal

This paper is submitted for publication and is therefore not included.

V

Paper VI

Decarbonising the European energy system in the absence of Russian gas: Hydrogen uptake and carbon capture developments in the power, heat and industry sectors

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Abstract

Hydrogen and carbon capture and storage are pivotal to decarbonise the European energy system in a broad range of pathway scenarios. Yet, their timely uptake in different sectors and distribution across countries are affected by supply options of renewable and fossil energy sources. Here, we analyse the decarbonisation of the European energy system towards 2060, covering the power, heat, and industry sectors, and the change in use of hydrogen and carbon capture and storage in these sectors upon Europe's decoupling from Russian gas. The results indicate that the use of gas is significantly reduced in the power sector, instead being replaced by coal with carbon capture and storage, and with a further expansion of renewable generators. Coal coupled with carbon capture and storage is also used in the steel sector as an intermediary step when Russian gas is neglected, before being fully decarbonised with hydrogen. Hydrogen production mostly relies on natural gas with carbon capture and storage until natural gas is scarce and costly at which time green hydrogen production increases sharply. The disruption of Russian gas imports has significant consequences on the decarbonisation pathways for Europe, with local energy sources and carbon capture and storage becoming even more important.

Keywords: Stochastic programming, Energy transition, Carbon capture and storage, Hydrogen, Energy crisis

VI.1 Introduction

In the wake of the disruption of Russian gas supply to Europe, European Union (EU) policymakers are reshaping incentives and measures to reduce dependency on

Russian fossil fuels and maintain the pace of emission reduction and decarbonisation efforts (European Commission, 2023b). Sector-specific and cross-sectorial plans are being rolled out to adapt implementation plans for decarbonisation and electrification, promote necessary technology developments, and ensure the economic viability of transition with a sharpened competition for clean energy. Recently, the EU launched the Net-Zero Industry Act (European Commission, 2023a) as a part of the Green Deal Industrial Plan, promoting regulatory conditions that facilitate faster scale up of technologies that are crucial for sectors that must reach net-zero by 2050, such as wind and solar, renewable hydrogen and CO_2 storage.

The disrupted Russian gas supplies and geopolitical instabilities increase energy scarcity in the European energy market and reinforce the price pressure and volatility for both fossil and renewable energy. Competition for clean energy increases, while limitations in the availability of rare and vital metals together with supply constraints create delays and cost challenges for several large-scale renewable energy projects. The prevailing energy crisis and rapidly evolving energy landscape in Europe present ambiguous energy transition trajectories, especially with sustained removal (Pedersen et al., 2022) of Russian gas supplies. A large share of hydrogen is a recurring scenario,, e.g., Seck et al. (2022), yet to the best of our knowledge little studied upon disruption of Russian gas supply. Several European countries have reoriented to LNG imports, while the ambitions for penetration of hydrogen as a clean fuel are maintained (European Commission, 2023b). Current estimations for future hydrogen consumption appear to be at odds with emerging data (van Rossum et al., 2022). The impact of limited energy supplies on prioritisation of and strategies for remaining possible decarbonisation options should thus be lifted. Pedersen et al. (2022) addressed this topic, focusing particularly on cross-sector distribution of capacities and use of renewable energy across sectors to adhere with the 1.5°C climate target. They showed that the 1.5°C target can be maintained without Russian gas supplies, while a 2°C target is greater affected. Mannhardt et al. (2023) explored the effects of collective demand reduction across sectors as a response to disrupted Russian gas supply, with the objective of reducing energy consumption. Klaaßen & Steffen (2023) used a meta-analytical approach to explore shifts in needed power and transport investments to maintain climate targets as a consequence of Russian gas removal in EU.

This paper broadens the impact analysis of persistent removal of Russian gas supply, focusing particularly on the uptake hydrogen and Carbon Capture and Storage (CCS) in the power, heat and industry sectors. To this end, endogenous hydrogen demand modelling in energy system modes is needed to achieve more accurate projections. Such an integration has so far been overlooked in the scholarly discourse. The open-source power-system model EMPIRE model (Backe et al., 2022) is applied and its scope is extended by enhancing its analytical capability to scrutinise the role of natural gas and hydrogen in the prospective European energy infrastructure. Originally designed for long-term European power system expansion planning, the EMPIRE model has since been augmented to encapsulate CCS (Turgut et al., 2021), domestic heating systems (Backe et al., 2022) and hydrogen production (Durakovic et al., 2023b,a). Using EMPIRE, our focus rests on the modelling of hydrogen production technologies, which include electrolyser and natural gas reforming processes both with and without CCS, while considering scarcity of both electricity and natural gas. Furthermore, we evaluate energy consumption and the feedstock requirements of major industry sectors, such as cement, steel, ammonia, and refinery. The modelling approach for the power and heat sectors is informed by Backe et al. (2022), while the energy consumption figures for the transport sector are derived from external references. Our methodological approach seeks to illuminate the fuel and feedstock switch from natural gas to hydrogen within the future European energy system. To maintain the tractability of the model, we employ linear programming while retaining existing features of the EMPIRE model, including the handling of short-term uncertainty and multi-period investment planning.

The main contributions in this paper include: (1) the incorporation of endogenous hydrogen demand within a large-scale, long-term energy system investment model, (2) detailed modelling of the energy consumption and feedstock demand in key industry sectors, and (3) a comprehensive analysis of the influence of natural gas price and availability on hydrogen production, and the subsequent decarbonisation implications for the power, heat, and industry sectors in Europe.

The structure of the paper is as follows: Section VI.2 furnishes background information concerning the industry sector's role in energy systems, the prospective impact of hydrogen, and the use of CCS. Section VI.3 elucidates the adopted methodology and data sources. Section VI.4 presents and interprets our computational results. Finally, Section VI.5 provides concluding thoughts and directions for future research.

VI.2 Literature review

In the following, we present a brief overview of relevant literature on the energy consumption and decarbonisation of the industry sectors and its representation in energy system planning models, demand side flexibility in industry sectors, and the potential role of CCS and hydrogen in the industry sector.

VI.2.1 The industry sector in the energy system

In 2021, the industry sector accounted for 25.6% of the final energy consumption in the EU (European Environment Agency, 2023). It was the third largest energy consumer among all sectors. Also, the industry sector accounted for 22% total emissions in the EU with 757 million tonnes CO_2. Therefore, it is important to decarbonise this sector. An optimisation model for the simulation and operational optimisation of the industry sector with a high level of detail was developed (Wiese & Baldini, 2018). This bottom-up model was demonstrated in the Danish energy system. The pathway of the energy transition is simulated but not optimised. Although these models include sufficient operational details, the optimal investment for the transition in the industry sector was not investigated. In this paper, we aim to fill this gap by including the investment planning of the industry sector in a long-term stochastic energy system planning model. We focus on modelling the energy consumption of the industry sector, including cement, steel, ammonia and refinery. These are the major energy consumers in the industry sector. In the following, we present the background knowledge on modelling production processes in these sectors.

Cement production usually consists of raw materials handling, pyroprocessing, milling and bagging (European Environment Agency, 2019). The CO_2 emits during the pyroprocessing phase, where the raw materials mix needs to be heated up to produce clinker. The detailed cement production processes were provided by Alsop (2019). Traditionally, the fuel used to generate heat is natural gas. Different CCS technologies in the cement industry were reviewed (Hills et al., 2016). The use of hydrogen in cement production is a relatively new area of study and represents an interesting pathway for decarbonising the cement industry. A techno-economic assessment of using by-product oxygen from water electrolysis in hydrogen production for CCS in clinker production demonstrates potential cost advantages and highlights considerations around supply reliability and transport distance (Nhuchhen et al., 2022). The papers included detailed cement production processes but were limited to the cement industry only. In this paper, we consider both hydrogen fuel switch and CCS, and include the decarbonisation of the cement industry in a large energy system planning problem.

The steel production process involves the extraction of iron from its ore, purification, and conversion into steel, typically through the blast furnace-basic oxygen furnace method or the electric arc furnace method. Steel-making and continuous casting is usually the bottleneck in iron and steel production. An integer programming model was developed to optimise this process by Tang et al. (2002). A techno-economic model was developed for evaluating four alternative primary steelmaking routes (Fischedick et al., 2014). The authors investigated the economic and technical viability of innovative primary steel production methods in Germany until 2100 by comparing three new ore-based steelmaking routes to the traditional blast furnace method. The study showed that with rising prices for coal and CO_2 allowances, blast furnace-based routes might become unprofitable, making hydrogen direct reduction and iron ore electrolysis economically attractive due to higher energy and raw material efficiency together with the potential to meet 80% reduction targets. However, high investment costs and electricity price dependency could hinder profitable implementation without further subsidies before 2030–2040.

Traditionally, natural gas is used as a feedstock for ammonia production plants to produce hydrogen locally via steam reforming and then produce ammonia from hydrogen (Egenhofer et al., 2014). Optimisation models for the production optimisation of chemicals can be hard to solve due to the inclusion of complex constraints. A trust region filter method for the black-box optimisation problem was proposed and was applied to solve an ammonia synthesis problem (Eason & Biegler, 2016). Here, due to the problem size and research focus, we simplified the modelling of ammonia production. In addition, we consider ammonia production from the purchased hydrogen from a hydrogen system.

Hydrogen is used to reduce the sulfur content of diesel fuel in the refinery industry. Traditionally, hydrogen is produced on-site with some emissions. A single objective optimisation model is proposed to maximise hydrogen production in an oil refinery at steady state condition (Sarkarzadeh et al., 2019). The study showed that the main advantages of the optimised process were the higher hydrogen production at lower steam capacity in the plant and higher hydrogen production in reforming and shifting reactors. A linear programming model was developed to optimise the hydrogen distribution network for the refinery industry, and an efficient network design has been achieved with a 30% reduction in hydrogen utility usage (Fonseca et al., 2008).

Most of the literature considered the optimisation of hydrogen production on-site, and the emissions from producing hydrogen were not sufficiently addressed. In this paper, we combine the refinery sector with other industry sectors and consider acquiring hydrogen from the system for the refinery processes.

The energy consumption of the industrial sector is a large share of the total energy consumption. However, in most of the existing energy system investment planning models, the industry is modelled simplistically. In Backe et al. (2022), the energy consumption is only modelled exogenously, and the energy transition in such a sector is not sufficiently modelled. In this paper, we aim to fill this research gap by including sufficiently detailed operational modelling of the industry sectors in a long-term energy system planning model and analyse the energy transition in the industry sector.

Due to the higher penetration of uncontrollable renewable energies, demand-side management has become an increasingly interesting and important topic. It is important to harness renewable energies better. There is a potential in the industry sector to shift their production activities according to energy availability. Zhang & Grossmann (2016) pointed out that the active management of electricity demand by power-intensive process industries is an important part of demand side management. A comprehensive review of the existing works on enterprise-wide optimisation for industrial demand side management was presented. As a major energy consumer, demand-side management in steel plants can help stabilise the power grid (Castro et al., 2020). The authors developed a new mixed integer linear programming model to optimise electric arc furnace operations in steel plants, showing that despite low electricity prices, high-power modes are largely avoided due to their less energy-efficient nature and higher electrode consumption, emphasising the importance of electrode replacement in reducing overall costs. In this paper, we include industrial demand-side flexibility, which can be a significant source of flexibility (Gils, 2014), by allowing each industry sector to shift their production by some percentage of their capacities.

VI.2.2 Hydrogen in energy systems

From the literature above, we can see that hydrogen can be used in multiple industry sectors, and in this paper, we systematically model the potential hydrogen demand in industry. In addition to providing fuel and feedstock for industrial production processes, hydrogen as a clean energy carrier can be used in other sectors, such as power and heat and can be important for the energy transition in general. We provide some literature on hydrogen in the energy transition in the following.

Cloete et. al (Cloete et al., 2022) investigated the potential trade channels for energy exporters in a low-carbon future using a new model. They found that natural gas imports with CO_2 capture is the least costly solution. However, exporting blue hydrogen or steel produced via hydrogen reduces CO_2 handling and is a viable diversification strategy for fossil fuel exporters like Norway, despite moderately higher costs. Moreno-Benito et al. (2017) extended the SHIPMod optimisation framework to develop a sustainable hydrogen infrastructure for the UK's transition towards a low-carbon transport system. The extended model includes economies of scale, road and pipeline transportation, and CCS technologies. The authors found that the most cost-effective hydrogen production method that maintains low carbon emissions is natural gas reforming with CCS. Bødal et al. (2020) proposed a cost-minimising model to optimise investments in electricity and hydrogen infrastructure under various low-carbon scenarios. They found that in Texas, by 2050, hydrogen produced from both electricity and natural gas is cost-effective for emissions reduction, offering system flexibility and enabling high renewable energy shares with less battery storage. However, the results showed that the shift from electrolysis to steam methane reforming for hydrogen production depends on carbon pricing and hydrogen demand. A mixed-integer linear programming model was proposed to use offshore energy hubs to produce and store green hydrogen offshore for the decarbonisation of the Norwegian continental shelf (Zhang et al., 2022b) and the European energy system (Zhang et al., 2022a). The REORIENT model was proposed to integrate investment, retrofit and abandonment planning in a single stochastic mixed-integer linear programming for the long-term planning of the European energy system (Zhang et al., 2023). The results showed that the REORIENT model could yield 24% lower investment cost in the North Sea region than the traditional investment-planning-only model.

Only a few published studies have explored the integrated natural gas, CCS and hydrogen value chains in multi energy system models. Sunny et al. (2020) developed a H2–CCS value-chain modelling framework as a resource task network, incorporating the specification of exogenous demand that can be satisfied using hydrogen and other alternatives. Hydrogen and CCS infrastructure was optimised, yet few details on the demand side, particularly the industry sector, were included, and the power sector was omitted in the model. Reigstad et al. (2022) analysed future hydrogen demand and infrastructure for hydrogen production, transport and storage with a specific focus on Germany, the UK, the Netherlands, Switzerland and Norway. The analysis also included the use of hydrogen and its combination with CCS for decarbonisation of both industry and transport, still with exogenous demand. The studies of Pedersen et al. (2022) and Victoria et al. (2022) applied the PyPSA-Eur-Sec model including options to invest in hydrogen production using steam methane reforming with or without CCS and electrolysis. Options for autothermal reforming with CCS, constituting improved efficiency and reduced CO_2 emissions were not included in the model. Resorting to a deterministic approach, stochasticity in renewable generation was omitted in the model and a 3 hour time resolution was used, thereby limiting the impact of variability in renewable generation in their analysis. Seck et al. (2022) analysed the potential of low-carbon and renewable hydrogen in decarbonising the European energy system according to the set EU targets, using a three-level, deterministic modelling approach with a detailed European TIMES-type model (MIRET-EU), an aggregated model for the European energy system, and a dedicated model for assessing hydrogen import options for Europe (HyPE). An emerging feature of this approach was the ability of endogenous cost reductions based on technology deployment in the model.

A comparison of this paper with relevant literature is presented in Table VI.1. In addition, for a more detailed literature review on hydrogen in energy systems, we

[1]This column marks the papers that include the development of the CCS transport chain, as well as the sequestration of CO_2.

[2]The natural gas column designates those papers that model the natural gas reserves and the production from these, or import from LNG terminals, along with transport through the natural gas pipeline network.

Table VI.1: Comparison of this paper with relevant literature.

Ref.	Optimisation	Multi-period	Stochastic	Power	Heat	Industry	Hydrogen	CCS[1]	Natural gas[2]
Seck et al. (2022)	X	X		X	X	X	X	X	
Sunny et al. (2020)	X	X			X	X	X	X	
Pedersen et al. (2022)	X	X		X	X	X	X	X	
Backe et al. (2022)	X	X	X	X	X				
Zhang et al. (2022a)	X	X	X	X	X		X		
Bødal et al. (2020)	X			X			X		
Fischedick et al. (2014)						X (only steel)	X		
Nhuchhen et al. (2022)						X (only cement)	X		
Fonseca et al. (2008)	X					X (only refinery)	X		
This paper	X	X	X	X	X	X	X	X	X

refer the readers to Agnolucci & McDowall (2013), who reviewed hydrogen literature across different spatial scales, and Li et al. (2019), who reviewed optimisation literature on hydrogen supply chains.

VI.3 Methodology and data

EMPIRE (Skar et al., 2016; Backe et al., 2022) is used in this paper, formulated as a multi-horizon (Kaut et al., 2014) stochastic (Birge & Louveaux, 2011) mathematical problem. EMPIRE minimises the investment and operational costs for power production, transmission, and storage. While EMPIRE was originally a power sector model, it has since been expanded considerably with an explicit model for the domestic heating demand (Backe et al., 2023), and also the production of green (Durakovic et al., 2023b) and blue (Durakovic et al., 2023a) hydrogen to meet an exogenous demand. In this work, EMPIRE has been expanded to include the option to develop a CCS chain, and it now includes the industry sector together with the hydrogen sector. With this change, hydrogen demand is no longer an exogenous input, as hydrogen is one of several energy carriers and industrial feedstocks that the model can choose. Also, the availability of natural gas is modelled explicitly with available resources, LNG terminals, and pipeline capacities. An introduction to how EMPIRE is generally set up is given in Section VI.B.

The two temporal scales in the multi-horizon framework are the long-term strategic periods, and the short-term operational hours. The strategic periods are each five years long, and EMPIRE can invest in new capacity for all assets at the start of each strategic period. The operational hours are linked to each strategic period, featuring hourly dispatch of the assets to meet the demand of each commodity, such as, e.g., power. EMPIRE represents each of the meteorological seasons with one representative week of hourly operations each, as well as two days of peak power demand. This temporal resolution is to validate the investments made in the strategic period, and the operational costs for these representative weeks and peak days are scaled up to represent the operational cost for one representative year. EMPIRE features uncertainty in its operations, where each operational scenario consists of such a representative year. There are three such operational scenarios in this work, where the uncertain parameters include renewable power generation and electric power demand.

EMPIRE features 52 nodes to represent the European energy system. 30 nodes are for countries in Europe, in addition to 5 nodes for the five power price zones in Norway. There are also 14 offshore wind farm nodes, and one offshore energy hub node as in Durakovic et al. (2023b). The remaining two nodes are the Sleipner and

Draupner offshore platforms, which are used to transport natural gas in the North Sea. The industries included in EMPIRE include the steel, cement, ammonia and oil refining industries, all of which have the potential for large-scale use of hydrogen in the future.

EMPIRE features a cap on annual CO_2 emissions, in line with the targets set by the European Commission (2018). Whereas the European Commission separates the CO_2 emissions from the power and industry sectors, in EMPIRE, these separate caps are added into one shared cap for all sectors, giving the model the freedom to trade emissions across sectors if necessary.

Previously, natural gas was assumed to be abundant, and following the price as reported by the European Commission (2016). This has changed in this work in order to reflect the lack of Russian natural gas in the energy system. Instead, the production and transmission of natural gas are now modelled explicitly in EMPIRE, where production can occur in Russia, North Africa or in the North Sea. No new pipeline capacity or Liquid Natural Gas (LNG) import capacity can be built, where the existing pipeline capacity is taken from ENTSO-G as implemented by Egging-Bratseth et al. (2021), and the LNG capacity of each country is as reported by Gas Infrastructure Europe (2022). All reserves estimates are taken from bp (2021), except for the Norwegian reserves, which are allocated to the three south-western price zones based on geographic location as reported by Norwegian Petroleum (2023). Furthermore, in the cases where Russian gas is included, it is assumed that there is an unlimited supply from Russia, and the only limiting factor is the pipeline capacity. Similarly, LNG supply is also assumed to be inexhaustible, and is only limited by the import capacity. The production capacity of Norway is split into the three power price zones, where the production capacity of the price zone is the capacity of Kårstø (Equinor, 2023) in NO2, of Nyhamna (Gassco, 2023) in NO3, and of Kollsnes (Equinor, 2023) in NO5. The natural gas production capacity of the UK was taken from the Energy Information Administration (2022). The natural gas coming from North Africa is assumed to be constrained by the pipeline capacities into Spain and Italy, and so these are the limits for this source. To represent the flexibility in the North Sea pipeline network, the two hub platforms Sleipner and Draupner are also represented, thereby representing the North Sea gas pipeline network similarly to Kazda et al. (2020). These are initially powered by on-site gas turbines, and have the option of electrification from mainland Norway. Some countries also have long-term natural gas storage, with the total capacity for this taken from the European Commission (2022a).

Cost of producing natural gas is assumed to be the same in the North Sea, Russia and North Africa, and every country is assumed to pay the same price for LNG. These prices are uncertain, and so two cases a constructed, where the natural gas is more costly in one case. In the affordable case, natural gas production is assumed to cost 10 EUR/MWh, and in the costly case, this cost is doubled to 20 EUR/MWh. The LNG prices are summarised in Table VI.2.

The CCS chain is modelled such that CO_2 can be captured from certain power generators fuelled by coal or natural gas, from hydrogen production with natural gas reforming and from certain industry plants, when applied in the steel and cement sectors. CO_2 can be transported internationally using pipelines, and can only be permanently sequestered in the North Sea. Table VI.3 shows which nodes can sequester CO_2 in this work, and the corresponding maximum capacity for

Year	Affordable LNG	Costly LNG
2020	20.86	50.98
2025	22.57	55.15
2030	24.55	59.98
2035	26.22	64.06
2040	27.10	66.22
2045	27.66	67.57
2050	28.08	68.62
2055	28.08	68.62

Table VI.2: Price for LNG in affordable and costly case

Node	CO_2 sequestration capacity [Gt]	Reference
NO2	29.5	Halland et al. (2022)
NO3	30.7	Halland et al. (2022)
NO5	0.2	Halland et al. (2022)
Denmark	0.3	Turgut et al. (2021)
The Netherlands	4.0	Turgut et al. (2021)
Great Britain	78.0	Turgut et al. (2021)

Table VI.3: Maximum capacity for offshore CO_2 sequestration in the North Sea.

sequestration.

The industry is represented by the steel, cement, ammonia and oil refining industries. The yearly output of steel is taken from the European Parliamentary Research Service (2021), where the future growth is assumed to follow the growth trajectory as reported by the International Energy Agency (2020). The initial capacity of each country is taken from EUROFER (2019). It is assumed that the total scrap use cannot exceed 45% of the total annual crude steel demand, which is roughly the average share of electric arc furnace production in Europe from 2012 to 2021 (EUROFER, 2022).

Ammonia demand is taken from Egenhofer et al. (2014). For the initial capacity, it is assumed that this demand is met as if all of it were produced by ammonia plants with local Steam Methane Reforming (SMR) without CCS, and that the capacities of these initial plants are as if they meet the yearly demand by producing at maximum capacity all year. The alternative way to produce ammonia in this model is to have an ammonia plant that receives hydrogen from the hydrogen market rather than producing it locally.

Cement is another sector that can potentially benefit from hydrogen and CCS, especially the latter as the decomposition of limestone to calcium oxide in clinker production emits roughly 0.78 tons of CO_2 per ton of clinker produced. These emissions also occur even if the fuel in the kiln is completely emissions free. In this model, the yearly demand for cement is taken from the US Geological Survey (2021), where the clinker to cement ratio is assumed to be improved as described by the International Energy Agency (2018). The present capacity is assumed to be such that the yearly demand is met by the initial capacity is run at maximum capacity all year long.

Refineries consume significant amounts of hydrogen and are included here as an industrial sector. McKinsey Energy Insights (2022) gives the refinery production capacities of each European country, which is used to meet the demand for refined oil. This demand is falling as Europe is decarbonising, and the yearly demand for refined oil is decreased based on the decrease of refinery runs in as reported by the International Energy Agency (2021).

The transport sector is modelled in a simplified way such that the annual energy demand for each energy carrier, as reported by the European Commission (2020), is met. The transport sector is thus an exogenous demand, and the model makes no decisions about the technologies that are used.

The full code and all data is available as open access on the public project Github page (Durakovic, 2023).

VI.4 Results and analysis

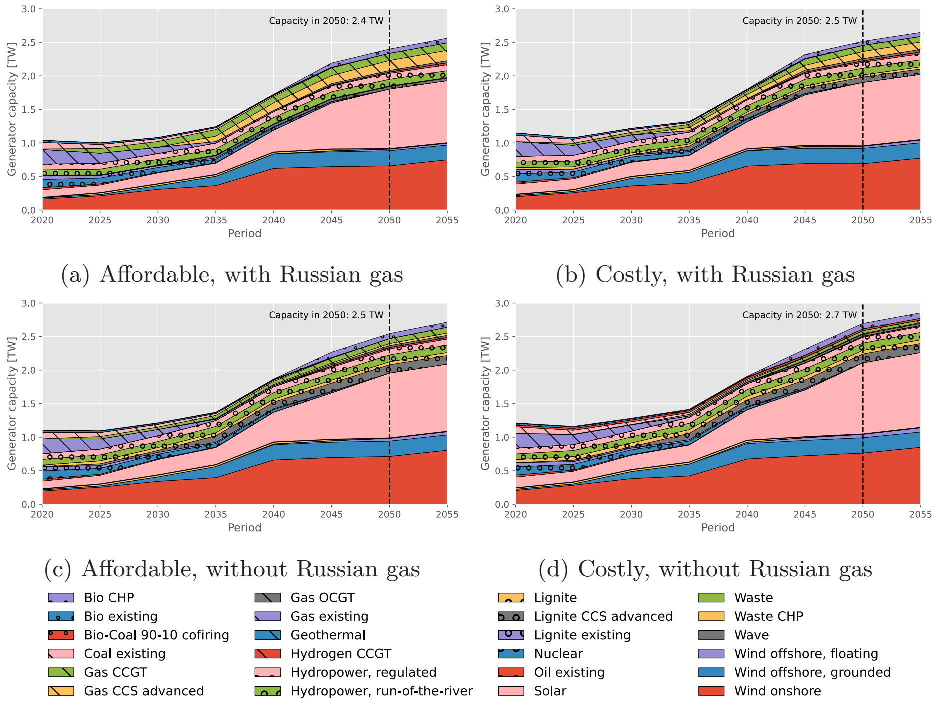
This section includes the results and analysis of these. Four cases are considered, featuring the different permutations of affordable and costly natural gas, and with and without Russian natural gas. Section VI.4.1 focuses on the temporal development of the power and domestic heat sectors, Section VI.4.2 analyses how the development of hydrogen production changes between the different cases, Section VI.4.3 shows the changes in industrial production for the cement and steel industries, and finally, Section VI.4.4 shows the utilisation of CCS.

VI.4.1 Power & domestic heat sectors

The European power demand is predicted to increase considerably in conjunction with tightening CO_2 emission caps. Figure VI.1 shows the development of the European power generation capacity, subject to these two developments.

The four cases shown in Figure VI.1 share some similarities. The first is that there is a large growth in power generation capacity in Europe, by at least 130% between 2020 and 2050. The second important observation is that this growth is mainly underpinned by the renewable generators of solar and wind. Furthermore, both onshore and offshore wind play large roles in the power system in 2050, where grounded offshore wind accounts for most of the offshore wind capacity, but floating offshore wind still has between 24.0 and 49.7 GW of capacity, depending on the case. Renewable power generators are thus at the core of the European power sector, with other dispatchable generators supplementing the renewables when there is insufficient renewable power generation to meet all demand. All four cases also feature hydrogen-fuelled power generators, but these only play a minor role, where the capacities total capacity for hydrogen-fuelled generators in 2050 is between 13.0 and 22.4 GW.

There are also some important differences between the cases in Figure VI.1. One trend that can be observed is how the total power generation capacity grows as access to natural gas is restricted, either through higher natural gas costs, or by removing Russian gas. Comparing the most relaxed case in Figure VI.1a with the most restrictive case in Figure VI.1d, it can be seen that the total power generation capacity in 2050 grows from 2.4 TW to 2.7 TW, or by about 12.5%. It can also be



(a) Affordable, with Russian gas

(b) Costly, with Russian gas

(c) Affordable, without Russian gas

(d) Costly, without Russian gas

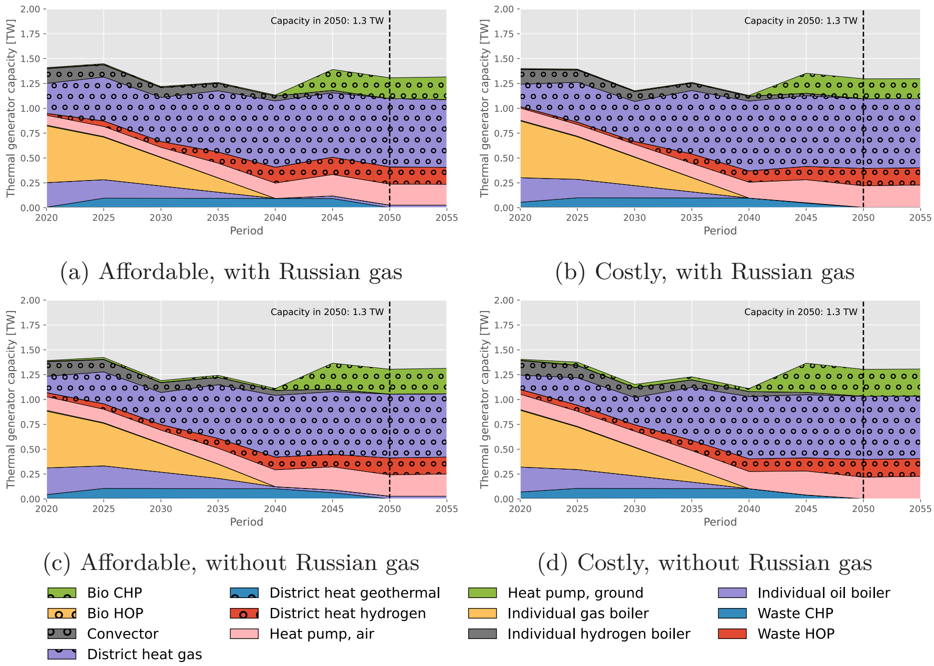
Figure VI.1: Development of European power sector.

observed how the total installed generation capacities of the renewable generators grow considerably as access to natural gas is restricted, with onshore solar and wind having the largest increase.

Another important difference between the four cases is the role of natural gas in the power sector. In Figures VI.1a and VI.1b natural gas power generators, both with and without CCS, account for a significant share of the power generation capacity, whereas in Figures VI.1c and VI.1d these capacities are strongly diminished. The power system requires dispatchable power that gas-powered generators previously offered, and in Figures VI.1c and VI.1d, this role is filled by coal-fired power plants with CCS. Furthermore, as previously discussed, renewables account for a larger share of the power generation capacity.

Figure VI.2 shows the development of the European domestic heat sector in the four cases. Overall, the development is very similar in all cases. It can be observed how the domestic heat sector tends towards larger centralised Combined Heat and Power (CHP) and district heat systems. The decentralised gas-based systems are simultaneously phased out. There is also a pivot towards individual air-source heat pumps, as opposed to boilers for individual households. Note that the capacity shown for heat pumps in Figure VI.2 is the electric capacity of the heat pump, as the coefficient of performance is stochastic, depending on the outside temperature in each country. The coefficients of performance are between 1.83 and 3.33. The heat output of the heat pump systems is thus higher than suggested by Figure VI.2.

Inspecting the differences between the cases, it can be seen how when access



(a) Affordable, with Russian gas

(b) Costly, with Russian gas

(c) Affordable, without Russian gas

(d) Costly, without Russian gas

Figure VI.2: Development of European domestic heat sector.

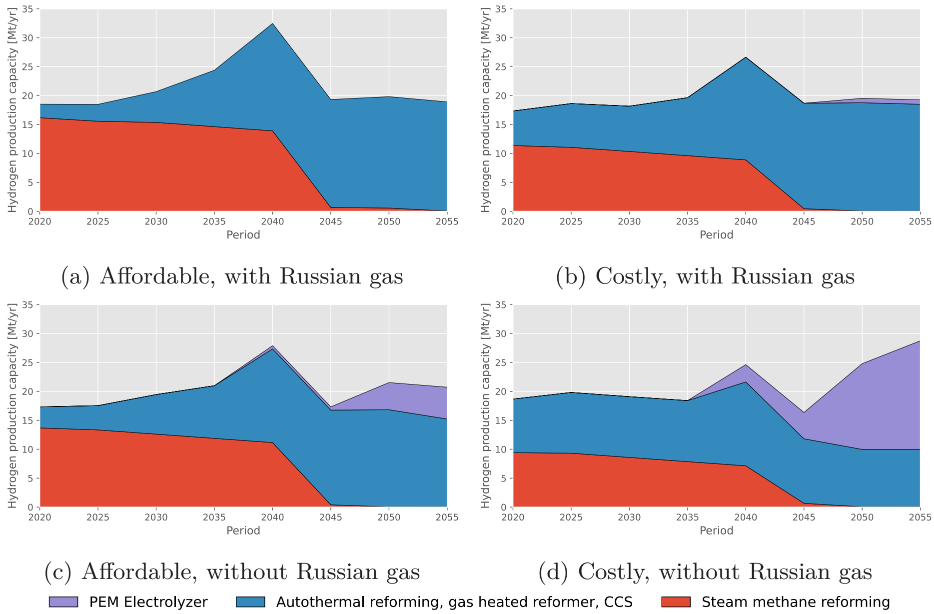
to Russian gas is removed, then there is a larger reliance on bioenergy-based CHP plants, where the capacity in 2050 increases by at least 18% compared to the respective case with Russian gas. The expanded use of heat pumps is in line with the results presented by Pedersen et al. (2022), but the use of hydrogen in the heat sector is not. In their results, hydrogen is not used in the heating sector at all, while electricity-based heat, from both heat pumps and resistive heating, is used extensively. One reason for this difference may be that their model is deterministic, thereby potentially overestimating the availability of renewable electricity. Taking the uncertainty of renewable generation into account has been shown to favour dispatchable generators (Seljom & Tomasgard, 2015).

In short, Figures VI.1 and VI.2 show how energy production for both power and heat rely more on energy sources within the EU, in terms of renewable energy generation, bioenergy, and to some extent, coal. This comes at the expense of gas use, which was previously in large part sourced from Russia.

VI.4.2 Hydrogen production

Hydrogen is an important energy carrier in a decarbonised energy system, where it can be used to decarbonise power and heat supply, as well as energy and feedstock supply in industry. Hydrogen is also used in the exogenous energy demand in transport, which has to be met in this model. Figure VI.3 shows the development of hydrogen production, as it is decarbonised along with the rest of the energy system, including the locally produced hydrogen for ammonia production, which is included in the steam methane reforming group.

Figures VI.3a and VI.3b show that when Russian gas is available, the most cost-effective way to produce hydrogen is through natural gas reforming. In the beginning, this hydrogen production is mainly based on SMR without CCS, much like hydrogen production today, but this way of producing hydrogen is substituted by autothermal reforming in the long term, using gas heated reformers for improved efficiency and CCS for reduced CO_2 emissions.



(a) Affordable, with Russian gas

(b) Costly, with Russian gas

(c) Affordable, without Russian gas

(d) Costly, without Russian gas

Figure VI.3: Development of hydrogen production capacity in Europe.

Interestingly, there is no substantial electrolyser capacity in either the affordable or costly case when Russian gas is available. This is because there is an abundance of affordable pipeline gas, and the included technologies are able to produce hydrogen with a very high CO_2 capture rate, allowing for the production of hydrogen with very low greenhouse gas emissions. At the same time, it is assumed that the delivered natural gas is not associated with any methane leak, whereas in reality, certain countries have considerable methane emissions associated with natural gas production, including for example Russia and Algeria (International Energy Agency, 2023). Accounting for the greenhouse effect from these methane leaks can have a significant impact on the climate footprint of blue hydrogen (Howarth & Jacobson, 2021), which can significantly influence these results by facilitating an increased production of green hydrogen. In considering the greenhouse effect from methane leaks, it is important to differentiate on where the hydrogen comes from Romano et al. (2022), advantaging Norwegian blue hydrogen. These results are aligned with the 2022 report by Hydrogen4EU (2022), where upstream methane leak was considered in the development of a hydrogen supply chain. In this report, the distribution between blue and green in their *Technology Diversification* case was similar to what is seen in Figure VI.3d, emphasising the potential of blue hydrogen production.

Removing access to Russian gas, as in Figures VI.3c and VI.3d, leads to some important differences. While the development of hydrogen production capacity looks similar in the short timeframe, it can also be observed how green hydrogen plays a much more important role in these cases, especially in Figure VI.3d where natural gas is costly. In these cases, there is substantially less pipeline gas available in the market, and much of the natural gas demand is met through LNG imports. In the case shown in Figure VI.3c, the LNG is affordable enough that it is economical to produce blue hydrogen from LNG imports. However, in the costly gas case, this occurs much more rarely, and pipeline gas is the main source of natural gas for hydrogen production. Since there is much less pipeline gas available in the case shown in Figure VI.3d, it becomes much more attractive to produce hydrogen through electrolysis. By 2050, green hydrogen accounts for almost 60% of the total hydrogen production capacity in Figure VI.3d, as the green hydrogen production capacity increases in conjunction with the large increase of renewable power capacity seen in Figure VI.1d.

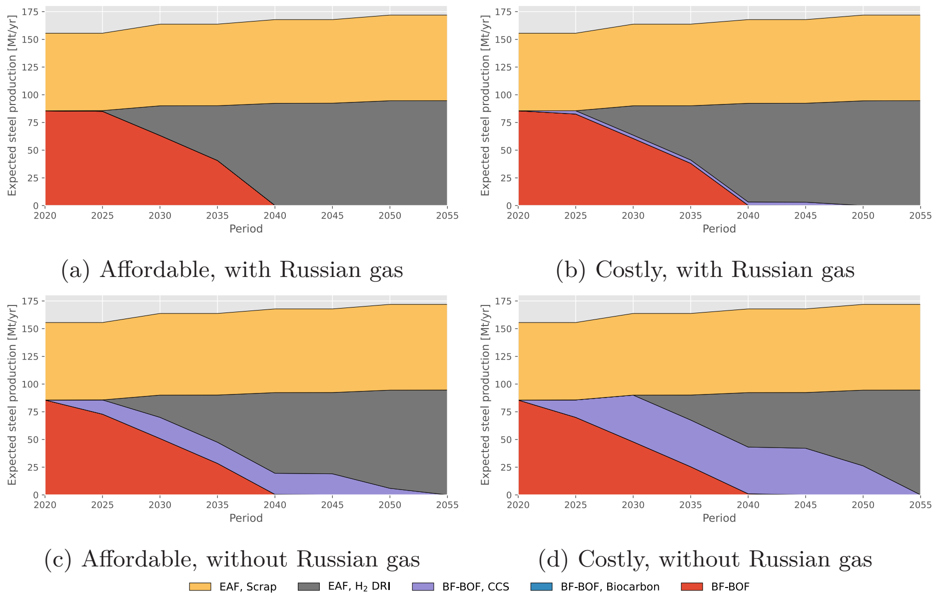
In the REPowerEU plan (European Commission, 2022b), the European Commission set a goal of 20 Mt of annual renewable hydrogen production, with 10 Mt being produced inside the EU, and the remaining 10 Mt being imported from nearby regions. None of the results shown in Figure VI.3 reach this goal. Instead, by 2030, all of the hydrogen production capacity is in natural gas reforming, and with the majority being SMR without CCS. Most of this capacity comes from local hydrogen production for ammonia. Considering the development of the power sector as shown in Figure VI.1, it is evident that by 2030 there is not enough renewable power to support 20 Mt of renewable hydrogen production. In order to achieve these goals, it is therefore necessary to build up a much larger capacity of renewable power generation by 2030. At the same time, the results suggest that this may not be necessary; it is possible to reach the carbon neutrality goals without needing 20 Mt of renewable hydrogen in 2030, and also without relying on Russian gas.

VI.4.3 Industry

This work includes the steel, cement and ammonia industries in order to cover their hydrogen demand, and see to what degree they use CCS, when possible.

Figure VI.4 shows the production of European steel, and the share of the total production that each steel plant accounts for. Common for all four cases is how the use of scrap is maximised, as this way of producing steel is emissions-free. Figure VI.4 also shows how eventually, regardless of the case, all European steel is made in Electric Arc Furnace (EAF) plants, that either use scrap or iron reduced using hydrogen as a feedstock. Biocarbon is also not used in any of the cases, instead favouring CCS and hydrogen as decarbonisation pathways.

The difference in the four cases mainly occurs as Russian gas is removed in Figures VI.4c and VI.4d. While also in these cases, steel production ultimately relies completely on hydrogen and scrap, the transition to this final state is different than the cases seen in Figures VI.4a and VI.4b. Whereas the cases with Russian gas transition directly from the conventional Blast Furnace, Basic Oxygen Furnace (BF-BOF) technology to hydrogen direct reduced iron with EAF, the cases without Russian gas go through an intermediate step with steel plants using the BF-BOF technology, but with CCS. This comes as a result of there being less affordable



(a) Affordable, with Russian gas

(b) Costly, with Russian gas

(c) Affordable, without Russian gas

(d) Costly, without Russian gas

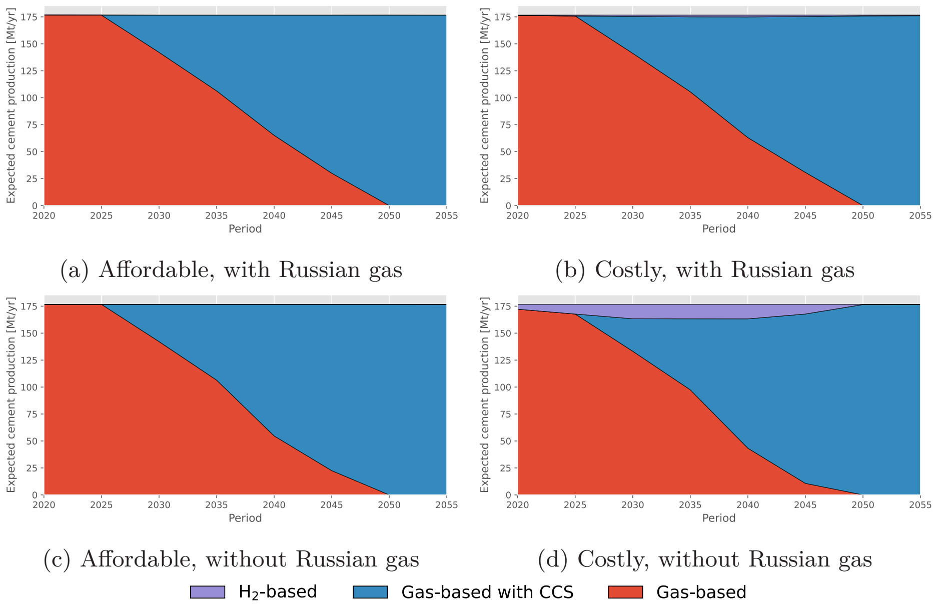
Figure VI.4: Evolution of European steel production.

hydrogen available in the energy system when the Russian gas is removed; it becomes more effective to decarbonise through CCS while the hydrogen market matures, even though the CO_2 capture rate in the steel sector is relatively low at 60%. In this way, the steel industry avoids having to use relatively scarce natural gas (through the consumption of blue hydrogen), and can instead continue using the more abundant coal.

In this work, the cement industry can be decarbonised by building cement plants where the clinker is produced using gas while capturing the CO_2 emissions, or partially decarbonised by switching the fuel used in clinker production to hydrogen. Figure VI.5 shows how these three options decarbonise the cement industry.

Comparing the four cases, it can be observed how their developments in the cement sector appear almost identical. Starting from 2030, the cement sector is gradually decarbonised by introducing CCS to cement plants, and by 2050, all cement plants feature CCS in all four cases. This result is in line with what is presented by the International Energy Agency (2018), where CCS appears as a priority for the decarbonisation of cement.

In Figure VI.5d, it can also be observed how a small share of clinker production experiences a fuel switch from natural gas to hydrogen before 2050. This result is counter-intuitive, as hydrogen production is largely based on natural gas, as seen in Figure VI.3d, and the production of this hydrogen includes an efficiency loss, thereby ostensibly introducing inefficiencies in the energy system. The reason for this fuel switch is a modelling anomaly. The hydrogen-based cement plants in the results are constructed in south-eastern Europe, a region that has previously been supplied by Russian gas. The availability of this gas is removed in this case. Furthermore, a modelling assumption is that the model cannot build new natural gas pipelines,



(a) Affordable, with Russian gas

(b) Costly, with Russian gas

(c) Affordable, without Russian gas

(d) Costly, without Russian gas

Figure VI.5: Evolution of European cement clinker production.

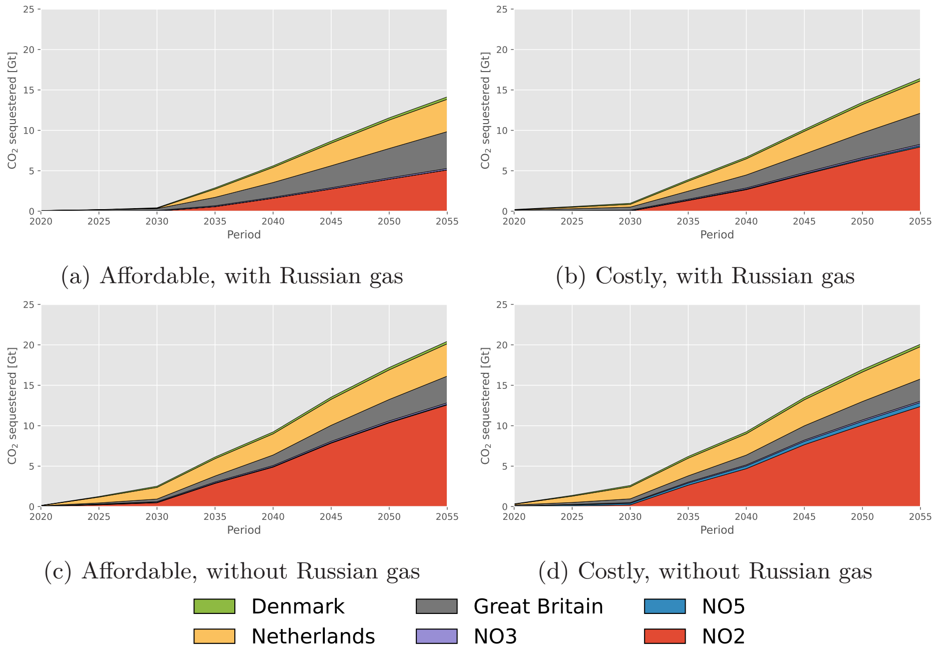
whereas it can build new hydrogen pipelines. As Russian gas is removed and LNG is (prohibitively) expensive, the existing natural gas pipeline infrastructure is not sufficient to sustain all the natural gas demand here. The model is thus forced to build hydrogen pipelines instead in order to meet the demand. This will in reality likely not develop as shown in Figure VI.5d, as the infrastructure may be operated in a more efficient way that is not modelled, or if necessary, the gas infrastructure may be reinforced to suit the needs of the energy system.

VI.4.4 Sequestration of CO_2

The results in this work use CCS on a large scale, and Figure VI.6 shows how much CO_2 is sequestered in the North Sea until 2055. It is evident that regardless of the case that has been investigated, CO_2 sequestration is an effective way to decarbonise the European energy system, and by 2050, at least 10 Gt of CO_2 has been sequestered in the North Sea.

Inspecting where the CO_2 is sequestered, it becomes clear that the geographic location of the sequestering site is important. The first areas to begin sequestering CO_2 are Denmark and the Netherlands, and these are also the only areas to fully utilise their maximum sequestration capacity. Following these two locations, the rest of the captured CO_2 is mainly stored in South-Western Norway, NO2, and Great Britain, owing to their proximity to continental Europe.

In the cases without Russian gas, shown in Figures VI.6c and VI.6d, CO_2 sequestration is used at a bigger scale than the cases with Russian gas, and at least 20 Gt of CO_2 is sequestered in these two cases. In Figure VI.1 it was shown that without Russian gas, the European energy system would rely more heavily on coal



(a) Affordable, with Russian gas

(b) Costly, with Russian gas

(c) Affordable, without Russian gas

(d) Costly, without Russian gas

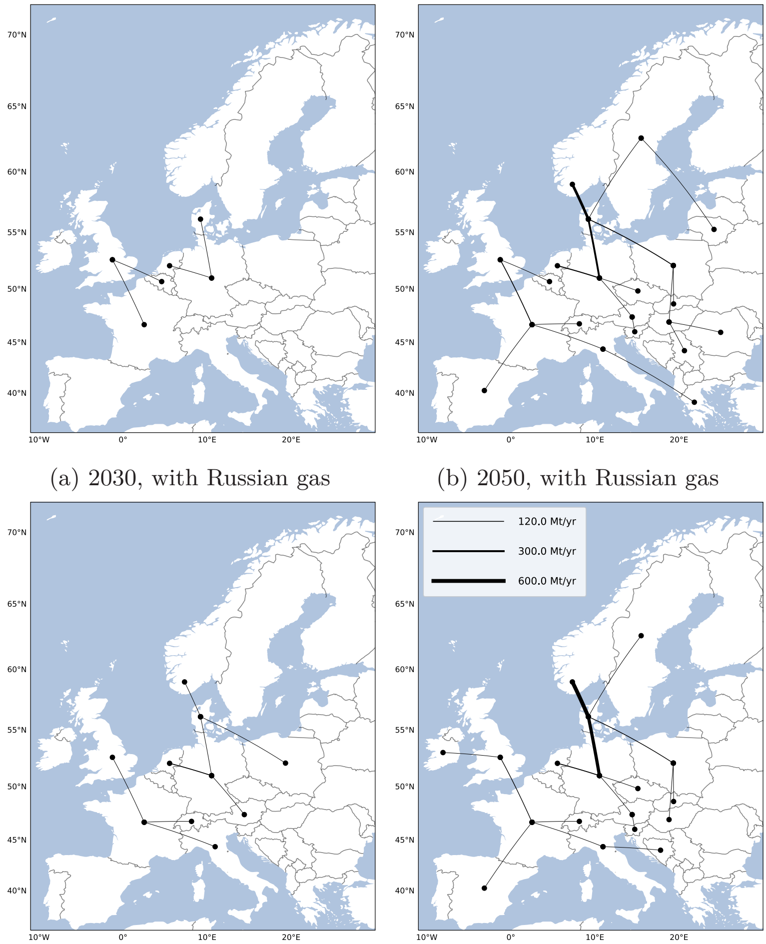
Figure VI.6: Expected cumulative amounts of CO_2 sequestered in the North Sea.

power plants with CCS, which capture more CO_2 per unit of energy than their gas-based counterparts. It was also shown in Figure VI.4 how CCS played a large role in the steel sector once Russian gas is unavailable, and the effect of these changes is that more CO_2 has to be sequestered in the North Sea, as shown in Figure VI.6.

Figure VI.7 shows the CO_2 pipeline topographies in 2030 and 2050 for the costly natural gas cases, with and without Russian gas. Broadly speaking, the topographies in 2050 look very similar for the cases with and without Russian gas, shown in Figures VI.7b and VI.7d. Here, the European countries are well-connected to each other, and with end-points in the main sequestration nodes, showing the importance of CCS in the future.

In 2030, some differences arise. Comparing Figures VI.7a and VI.7c, it can be seen how both cases show the start of the CO_2 pipeline networks seen in 2050, but also how the case without Russian gas, shown in Figure VI.7c, has a much more developed CO_2 pipeline network than the case with Russian gas. In fact, the sum of CO_2 pipeline capacities in 2030 in the case without Russian gas is over 3 times as large as the case with Russian gas. Furthermore, it is also evident how more countries have adopted CCS by 2030 in Figure VI.7c, and the topography is consequently more branched out.

CCS was predicted to be an important technology for the industry and power sectors (Holz et al., 2021), and it appears that it has become even more important following the disconnection from Russian gas. This applies both in the short term, as seen in the 2030 maps in Figure VI.7, but also in the long term, as demonstrated in Figure VI.6, where the total CO_2 sequestered by 2050 when there is no Russian



(a) 2030, with Russian gas

(b) 2050, with Russian gas

(c) 2030, without Russian gas

(d) 2050, without Russian gas

Figure VI.7: Development of CO_2 pipeline topography. All figures in the costly natural gas case.

gas significantly exceeds the cases when Russian gas is available.

VI.5 Conclusion

This work has investigated how the European energy system can reach the carbon neutrality targets by 2050 in the power, domestic low temperature heat, and industry sectors, while also accounting for the energy demand in the transport sector. The paper has analysed energy transition pathways without using Russian pipeline gas, and the results were compared with the case where Russian gas would again be available. An important contribution of the work is endogenous hydrogen demand modelling, enabling the model to optimise the deployment of technologies using hydrogen in the power and industry sectors, taking into account the scarcity of electricity and natural gas, which are required to produce hydrogen.

As a general conclusion from the results, hydrogen is projected a key role in the industry sectors going forward, and a minor role in the power system. The results show that hydrogen may also play an important role in the domestic heat sector, where it is used as a clean fuel for district heat networks.

The results also show a tremendous value of CCS in the decarbonised European energy system, especially now that Russian pipeline gas is not going to be used. With less affordable natural gas available, the European energy system relies more heavily on coal than it otherwise would, especially in the power and steel industries. This coal use is combined with CCS in order to significantly lower the CO_2 emissions.

Summarising the findings in key messages, it is found that:

- **The removal of Russian natural gas increases the use of coal.** It is found that in the power sector, coal power plants replace the role that gas otherwise would have as a dispatchable generator. In the steel sector, the use of iron reduced using hydrogen is also significantly delayed when Russian gas is unavailable, as the volume of affordable hydrogen in the energy system is insufficient. Consequently, BF-BOF steel plants fuelled by coal are used for longer. In both the power and steel sectors, CCS is used in order to decarbonise coal use.

- **The use of gas in the power sector is partially replaced by renewable power generators.** As access to natural gas becomes more restricted, by first removing access to Russian pipeline gas, and later increasing the price of LNG, it is shown how the generation capacities for the renewables grow considerably. In 2050, wind and solar account for most of the power generation capacity in all cases, but they play a much larger role when LNG is costly and Russian gas is unavailable.

- **Blue hydrogen production is a cost-effective way of producing low-carbon and affordable hydrogen.** Natural gas reforming, both with and without CCS, accounts for a large share of hydrogen production in all investigated cases, and in most cases it is the only source of hydrogen before 2050. Only when Russian gas is unavailable and LNG is very expensive does green hydrogen account for over half of the production capacity in 2050.

- **CCS is important for reaching European decarbonisation goals.** In all the investigated cases in this work, CCS plays a significant role in reducing European greenhouse gas emissions. This is especially the case in the power, hydrogen, and cement sectors. By 2050, at least 10 Gt of CO_2 is sequestered in the North Sea in all cases, with Great Britain, the Netherlands and South-Western Norway sequestering the most, owing to their geographic location and maximum offshore sequestration capacity.

- **Phasing out Russian pipeline gas increases the importance of CCS.** In the cases where Russian gas is removed, the minimum amount of CO_2 sequestered by 2050 increases to 15 Gt. Furthermore, it is shown that the

European CO_2 pipeline transport chain develops faster when Russian gas is unavailable. This is a result of how CCS is picked up in the steel industry, and also due to its use with more carbon-intense coal plants in the power sector.

There are several ways in which this work can be expanded and improved upon. These include:

- **Including endogenous handling of the transport sector.** This work has an exogenous transport demand for different energy carriers, including hydrogen, natural gas and oil. However, in following with the goal of the work to study the optimal uptake of different low-carbon energy carriers and fuels under different energy market conditions, it would also be worthwhile to treat the transport sector similarly to the other included sectors in this work.
- **Including additional industrial sectors in the model.** This work only includes four industries in the representation of the industry sector: steel, cement, ammonia and oil refining. There are other sectors that are also energy-intensive that are also covered by the ETS,, e.g.,, the aluminium sector. It would be interesting to also include these sectors in this work, to have a more complete representation of European industry.
- **Including long-term uncertainty.** Studying the European energy system until 2050 includes many uncertainties, especially long-term uncertainties when it comes to technology development and future policy. These uncertainties are undoubtedly important to planners today and in the future, and frameworks that include these uncertainties in their planning will be highly valuable. Future works should therefore look for ways in which these can be included while retaining the computational tractability of these problems.
- **Conducting a sensitivity on CCS parameters.** The results in this paper rely heavily on CCS, in all of the sectors that include this technology. However, CCS is not a mature technology yet. It would therefore be valuable to inspect how resilient this pathway is to alternative technological and economical developments in the CCS space. Moreover, studying different policies with regards to CCS acceptance would also be interesting.

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Appendix VI.A Nomenclature

Abbreviations

CCS	carbon capture and storage
EU	European Union
BF-BOF	basic furnace - blast oxygen furnace
LNG	liquid natural gas
SMR	steam methane reforming
CHP	combined heat and power
EAF	electric arc furnace

Indices

n, m	node
h	operational hour
i, j	investment period
ω	operational scenario
s	season
a	asset
c	commodity
p	production method

Sets

$\mathcal{I}$	investment periods
$\mathcal{S}$	seasons
$\mathcal{H}$	operational hours
$\mathcal{H}^F$	first hour of every season
$\mathcal{H}^L$	last hour of every season
$\mathcal{H}^s$	hours belonging to season s
Ω	set of scenarios
$\mathcal{L}^c_n$	all possible bidirectional arcs to node n for commodity c
$\mathcal{A}$	assets
$\mathcal{P}^c$	production methods for commodity c
σ^c	sinks of commodity c

Parameters

L^{period}	length of investment periods
α_s	scale factor for season s
A^c_n	total capacity for commodity c in node n
$D^c_{n,h,i,\omega}$	demand for commodity c in hour h in node n in scenario ω
$\bar{x}^a_{n,i}$	remaining initial capacity of asset a
i^{life}_a	lifetime of asset a

Variables

$x^a_{n,j}$	investment into asset a in node n in period i
$v^a_{n,i}$	available capacity of asset a in node n in period i
$v^{c,stor}_{n,i}$	available capacity of storage for commodity c in node n in period i
$y^{c,source}_{n,p,h,i,\omega}$	the production of commodity c in node n using production method p in hour h in period i in scenario ω
$y^{c,sink}_{n,h,i,\omega}$	the use of commodity c in other endogenous processes in node n in hour h in period i in scenario ω
$y^{c,trans}_{n,m,h,i,\omega}$	transport of commodity c from node n to node m in hour h in period i in scenario ω
$y^{ll}_{n,h,i,\omega}$	electric demand shed in node n in hour h in period i in scenario ω
$w^c_{n,h,i,\omega}$	storage level of commodity c in node n in hour h in period i in scenario ω
$y^{c,chrg}_{n,h,i,\omega}$	charging of storage for commodity c in node n in hour h in period i in scenario ω
$y^{c,dischrg}_{n,h,i,\omega}$	discharging of storage for commodity c in node n in hour h in period i in scenario ω

Appendix VI.B Introduction to EMPIRE

This appendix gives an introduction to the structure of EMPIRE, showing the logic of the constraints in the model. For an overview of symbols used in this appendix and their meaning, see Section VI.A.

Equation (VI.1) shows the general formulation of the flow balance for a commodity, c, in EMPIRE. The commodities covered by the flow balance constraints include the power, hydrogen, natural gas, CCS, transport, steel, ammonia, cement, and refinery sectors.

The flow balance consists of sources of a commodity, $y^{c,source}_{n,p,h,i,\omega}$, which are the various way in which the commodity is produced. For the power sector for example, the sources are the power generators, and for the natural gas sector, the sources include the various ways of producing or importing natural gas.

The sinks, $y^{c,sink}_{n,h,i,\omega}$, in the flow balance, are the endogenous uses of the commodity, and this links the different flow balances together. For example, to produce hydrogen with electrolysers, which is a source in the hydrogen flow balance, it is necessary to consume power, which is a sink in the power flow balance.

It is also possible to transport some commodities between nodes, which are covered by the two transport variables for import, $y^{c,trans}_{m,n,h,i,\omega}$, and export, $y^{c,trans}_{n,m,h,i,\omega}$. Some commodities, such as power, or the cases with inflexible industry, also have exogenous hourly commodity demands that must be met, represented by $D^{c}_{n,h,i,\omega}$. Where there is no such hourly demand, $D^{c}_{n,h,i,\omega}$ is set to 0. Finally, the power sector uniquely also has the option to curtail demand, which is covered by the variable $y^{ll}_{n,h,i,\omega}$.

$$\sum_{p\in\mathcal{P}^c} y^{c,source}_{n,p,h,i,\omega} - \sum_{sink\in\sigma^c} y^{c,sink}_{n,h,i,\omega} - \sum_{m\in\mathcal{L}^c_n}\left(y^{c,trans}_{n,m,h,i,\omega} - y^{c,trans}_{m,n,h,i,\omega}\right) = D^{c}_{n,h,i,\omega}\ (-\ y^{ll}_{n,h,i,\omega}), \quad n\in\mathcal{N}, h\in\mathcal{H}, i\in\mathcal{I}, w\in\Omega. \tag{VI.1}$$

Equation (VI.2) describes how for an asset a, the individual investments into capacity for that asset, $x^{a}_{n,j}$ and the remaining initial capacity of that asset, $\bar{x}^{a}_{n,i}$, sum up to the total capacity of that asset, $v^{a}_{n,i}$.

$$\sum_{j=i'}^{i} x^{a}_{n,j} + \bar{x}^{a}_{n,i} = v^{a}_{n,i} \quad n\in\mathcal{N}, i\in\mathcal{I}, i'=\max\{1, i-i^{life}_{a}\}, \quad a\in\mathcal{A}. \tag{VI.2}$$

An asset cannot be operated, $y^{a}_{n,i,h,\omega}$, at a higher level than its capacity, $v^{a}_{n,i}$,as described in Equation (VI.3).

$$y^{a}_{n,i,h,\omega} \le v^{a}_{n,i}, \quad a\in\mathcal{A}, n\in\mathcal{N}, i\in\mathcal{I}, h\in\mathcal{H}, \omega\in\Omega. \tag{VI.3}$$

Equation (VI.4) describes how storage is balanced for the commodities that have storage. In all hours except the first hour of each season, the storage balance simply says that the amount stored at the end of the hour, $w^{c}_{n,h,i,\omega}$, is the sum of the amount stored in the previous hour, $w^{c}_{n,h-1,i,\omega}$, plus the amount used to charge the storage in this hour, $y^{c,chrg}_{n,h,i,\omega}$, minus the amount discharged from the storage in this hour, $y^{c,dischrg}_{n,h,i,\omega}$.

For those hours that are at the start of a season, a starting amount stored is assumed. In this work, it is assumed that the storage starts half-full, $0.5 \times v_{n,i}^{c,stor}$. This is to allow enough flexibility for the model to charge and discharge the storage as it wishes, even during the start of the season.

$$w_{n,h-1,i,\omega}^{c} + y_{n,h,i,\omega}^{c,chrg} - y_{n,h,i,\omega}^{c,dischrg} = w_{n,h,i,\omega}^{c}, \quad n \in \mathcal{N}, h \in \mathcal{H} \setminus \mathcal{H}^{F}, i \in \mathcal{I}, \omega \in \Omega, \tag{VI.4a}$$

$$0.5 \times v_{n,i}^{c,stor} + y_{n,h,i,\omega}^{c,chrg} - y_{n,h,i,\omega}^{c,dischrg} = w_{n,h,i,\omega}^{c}, \quad n \in \mathcal{N}, h \in \mathcal{H}^{F}, i \in \mathcal{I}, \omega \in \Omega. \tag{VI.4b}$$

EMPIRE also features a constraint that ensures that the storage level at the last hour of the season is the same as in the start, to ensure that the storage does not lead to a net gain or loss of the commodity in the system. This is shown in Equation (VI.5).

$$w_{n,h,i,\omega}^{c} = 0.5 \times v_{n,i}^{c,stor}, \quad n \in \mathcal{N}, h \in \mathcal{H}^{L}, i \in \mathcal{I}, \omega \in \Omega. \tag{VI.5}$$

Some commodities have constraints that apply throughout the entire temporal horizon. This includes the natural gas reserves, where the sum of all natural gas production over all periods cannot exceed the local reserves of natural gas. Similarly, for CCS, it is not possible to sequester more CO_2 that the maximum capacity at that geographic location, A_n^c. This is described in Equation (VI.6), where the hourly operations are first scaled up to yearly values through the factor α_s, and then to the length of the period through the factor L^{period}. Note that the factor $(y_{n,h,i,\omega}^{c,sink}/y_{n,p,h,i,\omega}^{c,source})$ signifies that either there is a source of the commodity, as with natural gas, or there is a sink of the commodity, as with CO_2 in CCS.

$$\sum_{i \in \mathcal{I}} \sum_{s \in \mathcal{S}} \sum_{h \in \mathcal{H}^s} L^{period} \times \alpha_s \times (y_{n,h,i,\omega}^{c,sink}/y_{n,p,h,i,\omega}^{c,source}) \leq A_n^c, \quad n \in \mathcal{N}, \omega \in \Omega. \tag{VI.6}$$

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