Modelling Energy Systems with Variable Renewable Energy

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Thesis for the degree of Philosophiae Doctor (PhD)
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Scientific environment

This PhD has been carried out at the Geophysical Institute, University of Bergen. The work was funded by the University of Bergen, as part of a new initiative on energy transitions.

In addition to the research, this work has included the equivalent of one year of duty work. This time has been spent co-developing, administrating and lecturing the course *ENE101 Introduction to Energy Resources and Consumption*, as a teaching assistant in *ENE200 Energy Resources and Use*, and as a member of the research committee at the Geophysical Institute. A large portion of the work was also related to the administration of Bergen Energy Lab, including setting up, maintaining and creating content for their web pages, writing newsletters, and organising weekly meetings & half-day seminars.

I was also lucky to have spent six months during spring 2017 as a guest researcher at the Institute for Energy Technology (IFE), in Kjeller, Norway. In 2018, I attended the Young Scientists Summer Program (YSSP), at the International Institute for Applied Systems Analysis (IIASA), in Vienna, Austria. This three-month-long summer program received funding from the Norwegian Research Council.

During my PhD I have been part of the Norwegian Research School in climate Dynamics (ResCLIM) and its successor Research School on Changing Climates in the Coupled Earth System (CHESS). The wide variety of research-training courses and networking opportunities offered by ResCLIM and CHESS have been very useful.

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IFE

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Hans-Kristian Ringkjøb
Bergen, January 2020

Abstract

Today, the majority of anthropogenic greenhouse gas emissions stem from the burning of fossil fuels for energy purposes. In order to avoid devastating consequences of climate change, the world needs to reduce its emissions and transition its energy system to one based on low carbon technologies.

This transition has already begun. Renewable energy technologies, in particular solar and wind power, have seen massive growth in recent years, largely driven by political ambitions, cost reductions and technological improvement. However, since solar and wind are variable energy sources which depend on the weather for their electricity generation, challenges arise when they constitute a large part of the energy system.

Using long-term energy system modelling tools, this thesis focuses on gaining a better understanding of how to transition to a low carbon future, and how variable renewable energy technologies could be integrated into the energy system. Such tools are widely used to support policy, but many of them use a low temporal resolution that could be insufficient to represent solar and wind variability. One of the main objectives of this thesis is therefore to assess how such models treat solar and wind, explore how e.g. stochastic modelling techniques can improve their representation, and by extension contribute towards more robust decision making.

Two cases are modelled. First, pathways for how a remote isolated settlement in the Arctic can transition from a coal-based energy system to one based on renewable energy technologies are investigated. The results show that a stochastic modelling approach is needed to ensure a reliable energy supply, which could be based on solar and wind, energy storage, import of hydrogen and adequate back-up capacity. Second, a model of the European power and district heat sectors is used to explore the impact of modelling methodology and temporal resolution on model accuracy and performance. Here, the findings show that a stochastic modelling approach is preferred over deterministic models, even when the temporal resolution of the deterministic models is significantly increased. This case study also shows that a low carbon European power system is the preferred pathway going forward, with solar and wind, energy storage and cross-country interconnections as critical contributors.

This thesis demonstrates how energy modelling tools can be used to aid in the challenge of transitioning to a low carbon energy system with large shares of variable renewables, and presents techniques that leads to more robust results and a more accurate knowledge base for decision makers.

List of publications

1. **A review of modelling tools for energy and electricity systems with large shares of variable renewables**
   Ringkjøb HK, Haugan PM, Solbrekke IM
   *Renewable and Sustainable Energy Reviews **96**, 2018, doi:10.1016/j.rser.2018.08.002*
2. **Transitioning remote Arctic settlements to renewable energy systems - a modelling study of Longyearbyen, Svalbard**
   Ringkjøb HK, Haugan PM, Nybø A
   *Applied Energy **258**, 2020, doi:https://doi.org/10.1016/j.apenergy.2019.114079*
3. **Short-term solar and wind variability in long-term energy system models - a European case study**
   Ringkjøb HK, Haugan PM, Seljom PM, Lind A, Wagner F, Mesfun S
   Submitted to Energy, December 22, 2019

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Chapter 1

Introduction

In response to the threats of climate change, ambitious targets have been set to reduce global anthropogenic greenhouse gas (GHG) emissions. According to the IPCC [1], emissions must be halved by 2030 and reach net zero by 2050 in order to keep global warming below 1.5 degrees and to avoid catastrophic consequences for humanity. A key sector for achieving these targets is the energy sector, which is currently the largest contributor and responsible for about three quarters of global manmade GHG emissions [2]. There is an urgent need for shifting our energy supply from burning CO_2-emitting fossil fuels to using less carbon intensive resources. Simultaneously, an increase in the supply of energy services is needed. There are are still about 800 million people without access to electricity, and about 3 billion people rely on inefficient and polluting cooking systems [3]. Energy plays a vital role not only in fighting climate change, but also in combating poverty, hunger, promoting education, accessing clean water and to foster global sustainability.

Renewable energy can play an important role in decarbonising the energy sector. In recent decades, renewables have expanded at an unprecedented pace. In the EU, renewables now account for more than 30% of electricity generation, with wind power being the most important contributor [4]. Solar PV is still a small, but quickly growing, energy technology. Between 2010 and 2017, solar PV increased its generation in the EU five-fold from 23.3 TWh to 120 TWh [4]. During the same period, the cost of generating electricity from solar PV fell 73% and the cost of wind turbines halved [5]. In a recent study, Vartiainen et al. found that electricity generated from solar PV is already cheaper than the average spot price all over Europe [6]. The costs of solar and wind, as well as energy storage technologies such as batteries, are predicted to fall further [7, 8]. It is therefore likely that solar and wind will hold a large share of the electricity mix in the future [9, 10].

Solar and wind are, however, variable renewable energy sources (VRES), which depend on the sun to shine and the wind to blow for generating electricity. Integrating large shares of variable and partially unpredictable electricity generation in the existing energy infrastructure is therefore not straight forward, and will pose a severe challenge for today's power system. Measures such as flexible generation capacity, grid interconnections, energy storage and demand-side management can help accommodate VRES, but these require substantial infrastructure investments. It is evident that large changes in the energy system are needed, but it is not obvious which solutions and changes to the present system would give the highest benefit. Therefore, assessments on a system scale are needed.

1.1 This thesis

The overall objective of this thesis is to investigate how to facilitate for future low carbon energy systems with large shares of variable renewable energy sources. This involves how solar and wind variability is treated in energy modelling tools, and how this modelling can be improved for more robust decision making.

Energy modelling tools are often used to gain insights into the energy system, for strategic planning and to support policy-making. A number of tools exist, ranging from short-term operational models that treat the management of the grid on sub-second scales, to long-term integrated assessment models that treat multiple sectors of the economy several decades into the future [11]. Paper I of this thesis presents a comprehensive review of the state-of-art in modelling tools currently used both by the research community and industry. This review aims not only to summarize the capabilities and properties of various modelling tools, but also to help new modellers in identifying which tools could be appropriate for their needs and research questions.

One of the main motivations behind conducting the review was in fact to identify a suitable tool for further use in this thesis. Originally, it was considered to develop an energy model from scratch, but after discovering the many available models there was no reason for using a lot of time to reinvent the wheel. In order to study energy systems with large shares of renewables and how they are impacted by variable electricity generation, a model that could treat both the long-term evolution of the energy system while simultaneously addressing its short-term dynamics was desired. Long-term energy models fit this description perfectly. Several long-term energy models were considered, many of them having the same properties. Finally, the TIMES modelling framework was chosen. This was due to its documented and wide usage, its flexibility, and that it could help answering many of the research questions posed in this thesis. It was also helpful that the author was collaborating with researchers at the Institute for Energy Technology (IFE) who were using TIMES and were willing to share their expertise.

TIMES (The Integrated MARKAL-EFOM System) was developed by IEA-ETSAP (Energy Technology Systems Program) [12], and has been widely used to develop models of energy systems on various scales [13–15]. It follows a technology rich bottom-up approach, and uses linear programming to minimise total system cost over a given horizon, through optimal decision making on infrastructure investments, systems operation and imports of energy carriers. By modelling both the long-term evolution of the energy system and the short-term operations, TIMES is an effective tool for modelling the effects of VRES integration on various scales.

While long-term energy system models such as TIMES have been around for several decades, they face some challenges particularly in representing solar and wind variability. A large portion of this thesis is thus dedicated to explore how such models treat VRES, and how this representation could be improved. Two specific case studies have been investigated; the energy system in the small Arctic settlement of Longyearbyen, and the European power and district heat systems. Both cases are highly relevant for policy-makers, while at the same time excellent for studying the integration of variable renewables and the importance of an accurate modelling of solar and wind variability.

The structure of the thesis is as follows: Chapter 2 provides a general scientific background, with particular focus on the basics of long-term energy models, the stochastic modelling approach used in this thesis and how such models are applied in recent relevant literature to study the integration of variable renewables. In Chapter 3, the two models developed and applied in this thesis are briefly introduced, and results from an additional scenario that explores a 100% renewable European power mix are presented. Chapter 4 includes a list of the papers in this thesis and a summary of their contributions, with each of the papers appended at the end of the thesis. Finally, chapter 5 summarises the thesis and gives an outlook for future research.

Chapter 2

Scientific Background

The potential of renewable energy sources to replace fossil fuels has become a hot research topic in recent years. Several studies have assessed systems with very high or even 100% share of renewable energy [9, 10, 16–20], and several focus on the impacts of integrating large shares of variable generation [21–27]. A common feature of the majority of these studies is that they use some kind of modelling tool to aid and enhance their analysis.

Due to their dependence on the weather, the challenges that arise from integrating VRES occur on many timescales. This ranges from short-term operations on a sub-second scale to long-term planning several decades into the future. Constrained by computational capabilities, but also in order to address different purposes and capabilities, choices must be made on scope and resolution of models [11, 28, 29].

Figure 2.1 shows an illustration of the features of energy modelling tools, grouped into three overarching modelling types. Note that this is an illustration and not an accurate representation of the modelling landscape. Generally, models with high temporal resolution focus on the operational and technical aspects of the energy system, including challenges related to e.g. grid stability, load flow analysis or unit commitment. On the other hand, Integrated Assessment Models (IAM) combine the assessment of natural and man-made systems, linking for example the energy system to other economic sectors, effects on and by the climate and its impacts on land-use. Such models usually have a global scope and a long horizon of 50-150 years. IAMs are heavily used for policy analysis, especially in climate change mitigation studies, such as the IPCC's 1.5° scenario [1]. However, due to the wide scope of IAMs, their treatment of the energy sector is less detailed. When making infrastructure investment decisions in energy systems, especially those with large shares of variable renewables, as much operational detail as required should be included.

Long-term energy system models are a branch of modelling tools that attempt to deal with the long-term evolution of the energy system while still taking into account its short-term dynamics. For this thesis, where the aim is to model the transition to low carbon energy systems with large shares of variable renewables, long-term energy system models have many desirable properties (see the blue square in Figure 2.1).

The remainder of this chapter focuses on long-term energy models, particularly on

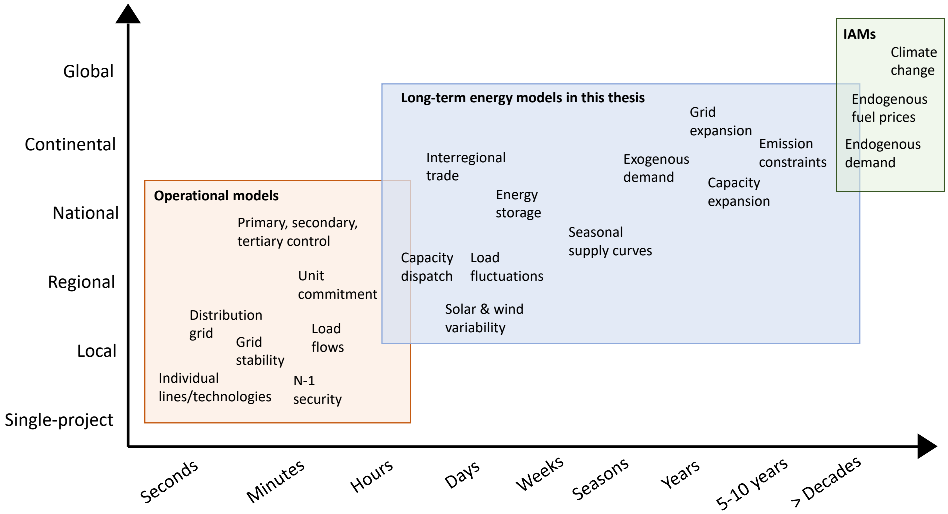

Figure 2.1: Illustration of the challenges assessed by various types of energy modelling tools. The figure is adapted from [30]

the TIMES modelling framework used in this thesis. Paper I of this thesis presents a comprehensive review of 75 modelling tools, including but not limited to long-term energy models.

2.1 Long-term energy system models

Long-term energy system models are often used to gain insights into the energy sector and to investigate transition pathways to future energy systems. Such models can encompass the entire energy sector, describing how energy carriers such as electricity or heat are produced, distributed and supplied to various end-use sectors, or they can also target specific sectors of the energy system, such as the power sector. Most models are flexible in terms of their spatiotemporal resolution, capable of modelling a wide range of system sizes, from small local energy systems to the entire global energy system, several decades into the future.

Usually, long-term energy system models are formulated as optimisation models, with the objective of minimising the total cost of providing energy services. In order to do this, the models make decisions regarding investments, operation and import of energy carries, and gives information about the optimal transition pathway, its costs, emissions and deployment of various technologies.

The knowledge gained from long-term energy models is valuable in policy-making. They can provide information about how to achieve desired future energy systems, or the likely evolution of the energy system given today's situation and assumptions about the future evolution of key parameters. These two ways of designing scenarios may be named prescriptive and descriptive, respectively [31]. Prescriptive scenarios are useful to understand what decisions are needed to achieve a given target. This could be a given target for CO_2 emissions, or to reach a given share of renewables in the energy mix. A descriptive scenario, on the other hand, could be used to investigate whether given policies (e.g. RES subsidies) would be sufficient to reach a stated goal, but without setting the goal as an explicit bound in the model. By doing this, such scenarios could be translated into actual policy portfolios that could be implemented in real life.

Despite providing useful knowledge, long-term energy system models should not be blindly trusted. The development of the energy system and decisions made in a model could strongly deviate from real-world dynamics and decisions. First, long-term energy system models make a number of assumptions of the evolution of key parameters, both in terms of future demand, technological characteristics, costs etc. The actual evolution will most likely differ from the modelled ones due to a number of factors such as unforeseen technological progress or political decisions. Second, optimisation models usually take a social planner's perspective, optimising to the benefit of the entire system rather than individual actors. In reality, individual actors might not act according to what is optimal for the entire system, but rather to their own benefit.

Long-term energy system models have been extensively applied to study various energy systems, and numerous models have been developed. Two well known examples are the MARKAL/TIMES [12, 32] and MESSAGE [33] families of models. TIMES has for example been used to study the decarbonisation of the UK [34, 35], Canadian [36], Chinese [37] or Californian [15] energy systems. Similarly, the MESSAGE model has e.g. been used to study the impact of wind power in southern Brazil [38], and to study power system reliability and how variability from renewable energy sources could be captured in a global Integrated Assessment Model [39]. Other examples include the open-source long-term energy models OSeMOSYS [24, 40] and Calliope [41–43], the National Renewable Energy Laboratory's (NREL) power system planning model ReEDS [44, 45], the U.S. Energy Information Administration's (EIA) NEMS model [46], or the PRIMES energy system model [47, 48]. Many of the above-mentioned models are actively used in policy-making. Both TIMES, PRIMES and MESSAGE have been widely used to support EU policies [34, 49, 50], while the NEMS model is used for EIA's Annual Energy Outlook [51].

2.2 The TIMES modelling framework

The fields of energy policy and energy modelling started gaining popularity after the oil crisis in 1973, when long-term strategic energy planning came on the agenda for both policy makers and industry [52]. The International Energy Agency (IEA), known for their annual World Energy Outlook (WEO), was established shortly after in 1974 as an international collaboration to foster energy security, energy efficiency and the development of alternative energy sources. Some years later, in 1976, IEA launched its Energy Technology Systems Analysis Program (ETSAP), with the aim of developing an energy system model that could aid government officials and decision makers to create robust and evidence-based energy and environmental policies [53]. This led to the development of the MARKAL (MARKet ALlocation) energy system model, which later evolved into the TIMES (The Integrated MARKAL-EFOM System) model.

TIMES is a modelling framework frequently applied to develop models for local, national, international or global energy systems [12]. An illustration of the TIMES model structure is shown in Figure 2.2.

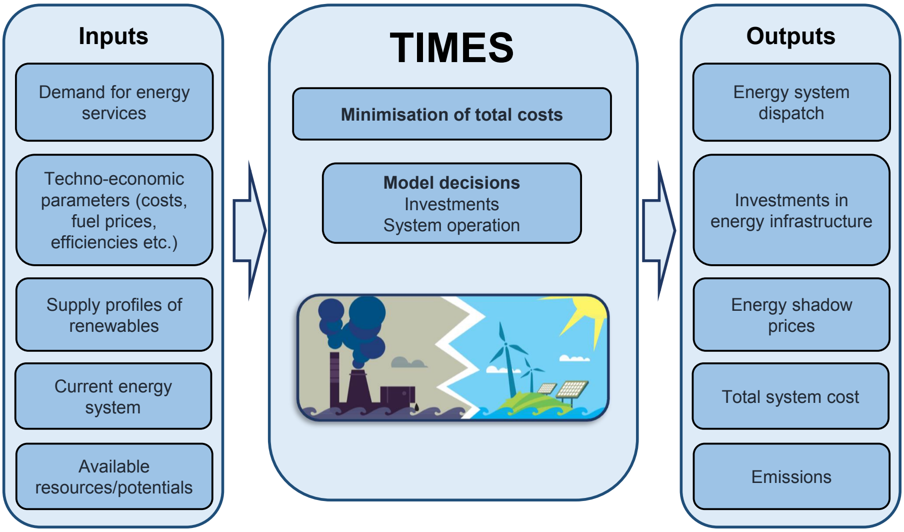

Figure 2.2: Illustration of the TIMES model structure (Figure inset: studioworkstock for www.colour-box.com)

It follows a bottom-up approach, and performs long-term analyses of the entire or parts of the energy sector. The TIMES modelling framework aims to provide energy services at the lowest cost possible, making optimal decisions regarding investments in infrastructure, operation of the system and imports/exports of energy carriers. It is built on linear programming, and equation 2.1 shows the objective function of an inelastic and deterministic TIMES model [12]:

$$
\begin{aligned}
& & & min(c^T \cdot x) \\
& subject\ to & & \sum_k A_{k,i}(t) \geq D_i(t), \qquad ; i = 1,\ldots,I; t = 1,\ldots,T \\
& and & & B \cdot x \geq b
\end{aligned}
\tag{2.1}
$$

The model minimises the discounted total system cost, where c is the cost vector and x is the vector of TIMES variables (the choices the model makes, e.g. new capacity additions or generation of energy commodities). The minimisation is subject to a series of constraints, where perhaps the most important one is is that the demand of various energy services (i) is met at all times (t). Here, $A_{k,i}(t)$ is the supply of energy from various end-use technologies (k), which has to be greater than or equal to the demand $D_i(t)$. Finally, $B \cdot X \geq b$ corresponds to all other TIMES constraints, for example the maximum installed capacity of a technology, emission constraints, minimum share of renewables in the energy mix and so on.

The decision-making in TIMES assumes perfect foresight (full knowledge of how market parameters will evolve across the planning horizon), perfect competition and is driven by the demand of energy services. A more detailed mathematical formulation of the TIMES modelling framework is out of the scope of this chapter, and can be found in [12].

The code for the TIMES model generator is available Open Source under a GNU General Public License v3.0., but requires commercial third-party software to be run [54]. This includes data and results handling software (ANSWER/VEDA) [54], and GAMS [55] plus a solver (e.g. CPLEX) to solve the model. The computational requirements to run a TIMES-based model depends strongly on the size of a given model. For this thesis, most runs were done on a normal laptop (Intel(R) Core(TM) i7-5600U CPU @ 2.60 GHz, 16 GB RAM), while some required a more powerful workstation (Intel(R) Xeon(R) Silver 4114 CPU @ 2.20 GHz, 96 GB RAM).

2.2.1 Temporal and spatial representation

Figure 2.3 shows an example of the temporal representation in a TIMES model. Here, the base-year to which all future costs and revenues are discounted to is 2015, and the modelling horizon is 2050. The planning horizon is divided into 9 time-periods, where investments are made every 5th year (the number of time-periods is flexible and can vary in length). Each time-period is represented by one milestone year, which is further divided into a set of user-defined time-slices that represent the hourly, diurnal and seasonal variations in supply and demand. In Figure 2.3, each milestone year is represented by 192 time-slices, distributed over 24 hours over two days (one weekday and one weekend day) per season; spring (March, April and May), summer (June, July and August), autumn (September, October, and November) and winter (December, January and February).

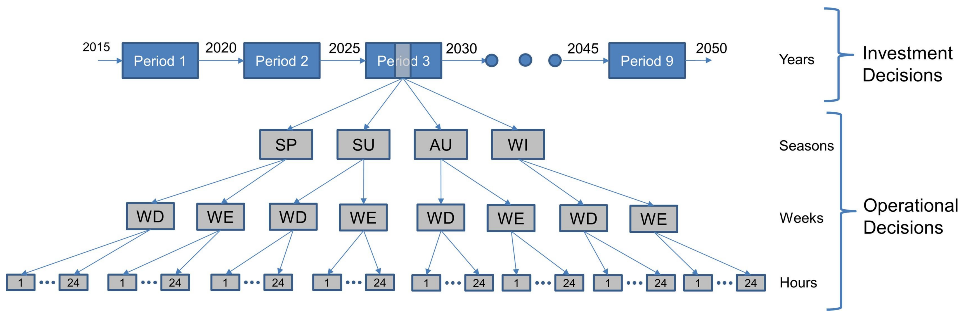

Figure 2.3: Typical temporal representation in a TIMES energy system model [56]

The flexible time-slice definition in TIMES is an advantage in comparison to its predecessor MARKAL. In MARKAL, time-slices were rigid and only permitted for electricity and low temperature heat, represented by six and three time-slices respectively [57]. The flexibility of TIMES allows a user to increase the number of time-slices, with the aim of improving the representation of various processes such as solar and wind power. However, increasing the temporal resolution of a long-term energy model also means increasing the computational demand, leading to a trade-off between modelling accuracy and computational requirements. A very common time-slice configuration in TIMES is to use 12 time-slices, used in e.g. the JRC EU-TIMES model [58]. However, to take into account the increasing share of intermittent solar and wind in the energy system, higher resolutions or other approaches to tackle solar and wind variability might be needed. This is further discussed in Paper III of this thesis.

The spatial resolution in long-term energy models varies greatly. Often, this depends on the scope of the given study, but there is also a trade-off between spatial resolution and computational demands. Splitting up a region into several sub-regions could improve the representation of local characteristics, such as resource availability and load centers. For example, Paper III of this thesis focuses on Europe where each country is modelled as one region (node). This simplification could undermine the spatial distribution of generation and demand, and miss potential bottlenecks. A concrete example is Germany, where bottlenecks between the windy north and the industrial south leads to congestion and overloading [59]. Treating each country on a national scale could therefore underestimate required upgrades of the distribution grid.

2.2.2 Energy system representation

This section aims to describe how an energy system in TIMES is usually modelled, including its structure, parameters and required input data. It is important to mention that TIMES is a so-called model generator, meaning that the underlying structure is the same in all TIMES models, but each model version varies based on their input data. In other words, TIMES is a framework with equations and constraints that allows a user to design a specific model for a given purpose and a given system. A standard TIMES model is usually made up by various processes (technologies), commodities and commodity flows [12]. By combining these, entire complex energy systems could be represented.

Processes describe the conversion of one commodity into another, such as how natural gas is converted to electricity in a gas-fired power plant. Here, natural gas and electricity are two examples of commodities, and the flow of natural gas going into the process and the flow of electricity going out of the process are commodity flows. The input/output ratio of these flows also describes the efficiency of the process, which is one of many technological parameters defined for each technology. Commodities do not necessarily have to be energy carriers, but could also be materials, emissions, monetary flows or energy services [12]. There are also two special types of processes in TIMES, used to model storage technologies and to model inter-regional trade. Storage processes allow commodities to be stored from one time-slice to another (in e.g. pumped hydro storage plants or batteries), and trade processes allow trading of commodities between regions (e.g. cross-country grid interconnections).

Figure 2.4 below shows an example of a very simple TIMES model, consisting of three processes and three commodities. Coal is first imported, before converted into electricity in a coal-fired power plant. This electricity is then used to power a heat pump which produces heat for households. Through expanding this simple model with additional commodities and processes, entire energy systems could be modelled.

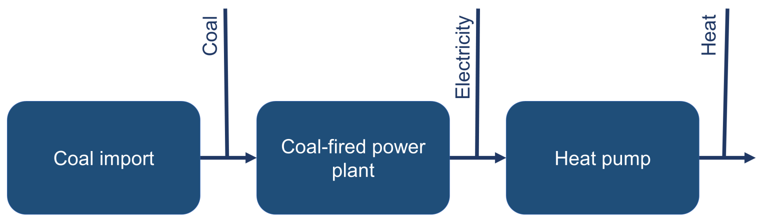

Figure 2.4: Representation of a very simple energy system in TIMES

In addition to the technological description of processes, their economic assumptions are also important input parameters to a TIMES model. Since the optimisation is cost-driven, the economic parameters decide whether a given technology is chosen in the solution or not. Therefore, the deployment of renewables is heavily dependent on their competitiveness with traditional fossil fuels. The cost of renewables have dropped massively in recent years, and are expected to continue dropping [6]. When modelling the energy system several decades into the future, it is important to capture their cost reductions going forward.

Projections of future demand for energy services are one of the most important drivers for model results, and are supplied exogenously to TIMES. Long-term energy models that cover all energy sectors, usually consist of a number of end-use sectors each with their own demand projection for various energy services. As an example, the demand in the transport sector could be defined as the number of passenger-kilometers. Then, the model has a choice of satisfying this demand through several technologies, e.g. an electric vehicle or a combustion engine vehicle. If the model decides to invest in electric vehicles, this will add to the demand for electricity in the model. Similarly, one could define the end-use sector of heating a household, with technology-choices such as heat pumps, biomass ovens or oil boilers, which in turn will affect the demand for the given commodity. As such, the demand for a given commodity such as electricity will be endogenous in an energy system model. As an example, TIMES-Norway consists of 70-80 end-use sectors that have a demand for energy services such as heating, cooling, electricity, vehicle-km etc. [60, 61].

In long-term electricity models, on the other hand, the electricity demand is usually supplied exogenously. For the two models used in this thesis, which include the electricity and district heat (DH) sectors, the electricity and DH demand is exogenous. However, electrification of heating, by for example using heat pumps or electric boilers that consume electricity to supply heat, will modify the demand for electricity.

2.3 Stochastic modelling in TIMES

Stochastic modelling in TIMES is a relatively new technique [62], first applied in a study of the Danish energy sector in 2015 [63]. Here, wind power was represented as a stochastic parameter, resulting in lower investments in wind power, lower energy system costs, less exports of electricity and an increased use of biomass in comparison to a deterministic model. Furthermore, Seljom & Tomasgard [64] studied the Scandinavian energy system with PV, wind, and hydro generation, as well as heat demand in buildings and electricity prices outside Scandinavia as stochastic parameters. Stochastic approaches have also been applied to other modelling tools than TIMES. An example is the model EMPIRE [65, 66], which covers the European power sector. The European power sector was also the focus of a stochastic model developed by Nagl et al. [67].

A stochastic long-term energy system model considers various operational situations caused by the short-term uncertainty of e.g. solar and wind [68]. This contrasts a conventional deterministic approach, which assumes that all input parameters are known. Generally, deterministic models are therefore optimised based on only one operational scenario where values of e.g. solar and wind availability are based on the expected outcome (climatology). By doing this, deterministic models make investments in an energy system that might not take into account the range of operational situations that can occur.

In a stochastic model, each uncertain parameter is represented by a set of possible realisations, called scenarios, and their associated probability of occurrence. Usually, these scenarios are generated through a scenario generation method, which will be further discussed in section 2.3.1. An example of the temporal representation in a stochastic model is shown in Figure 2.5. It is similar to that of a deterministic model (see Figure 2.3), but the stochastic modelling approach takes into account a range of operational scenarios that can occur.

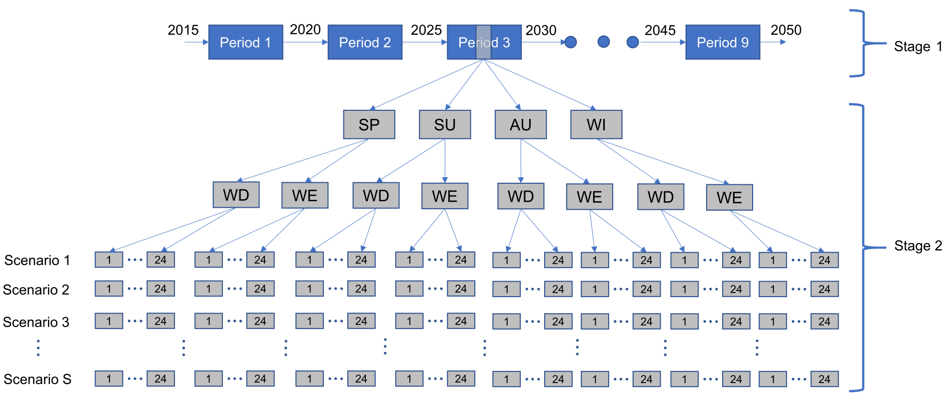

Figure 2.5: Illustration of the temporal representation in a stochastic long-term energy model

In a stochastic model, investment decisions and operational decisions are split into two separate stages. This division is important in order to define what information is known when certain decisions are made. During the first stage, investment decisions are made across all regions and throughout the whole modelling horizon. However, these investments are made without knowing the outcome of the operational scenarios, but takes into account their expected cost. The outcome of these operational scenarios is then revealed at the second stage, where operational decisions are made for each of the scenarios and for all model periods. This gives investments that take into account the expected operational cost, and are identical and feasible for all operational scenarios.

To do this a two-stage stochastic model is applied [68, 69], illustrated in Fig 2.6 through a scenario tree (as it is applied in paper III of this thesis). Often, this is also referred to as multi-horizon modelling, due to the division of the long-term and short-term dynamics in two separate stages [65]. A stochastic two-stage linear programming problem can be written as [70–72]:

$$\begin{aligned} & \min_x \; (c^T \cdot x + E[Q(x,w)]) & \\ \textit{subject to} \quad & A \cdot x \geq b, \qquad x \geq 0 \end{aligned} \tag{2.2}$$

Where x are the the first-stage decision variables, c^T the cost vector, $E[Q(x,w)]$ is the expected value of the optimal solution of the second stage problem, and $A \cdot x \geq b$ are the first-stage scenario-independent constraints. During the first stage, decisions have to be made before the outcome of the stochastic data w is known (a specific realisation of the uncertain parameter is called a scenario and noted w_s). The set of all realisations of the stochastic parameters is described by $\Omega = \{w_1, ..., w_S\} \subseteq \mathbb{R}^r$, where r is the number of parameters included. The second-stage solution can be written as [72]:

$$\begin{aligned} & Q(x,w) = \min_y \; d_w^T y(w) & \\ \textit{subject to} \quad & T_w x + W_w y(w) \geq h_w, \qquad ; y(w) \geq 0, \end{aligned} \tag{2.3}$$

Here, $y(w)$ are the second-stage decision variables, d_w^T is the uncertain parameter vector, T_w represents the transition matrix, W_w the recourse matrix and h_w the right-hand side of the second stage scenario-dependent constraints. Note that all decisions in the second-stage depends on the specific realisation of the stochastic data. If it is assumed that the uncertain parameters follow a discrete distribution, and that the probability of occurrence (p_s) for each scenario w is equal and sums to one for all $s = 1, ..., S$, then $E[Q(x,w)] = \sum_s p_s d_s^T y(s)$, where $y(s)$ is the optimal second-stage decision for scenario w_s [73]. The model can then be written as a large linear program, often called the deterministic equivalent [72–74]:

$$\begin{aligned} & \min_{x, y_1, \ldots, y_S} \; (c^T \cdot x + \sum_s p_s d_s^T y(s)) & \\ \textit{subject to} \quad & A \cdot x \geq b, \qquad x \geq 0 \\ \textit{and} \quad & T_s x + W_s y(s) \geq h_s, \qquad ; s \in S, y(s) \geq 0 \end{aligned} \tag{2.4}$$

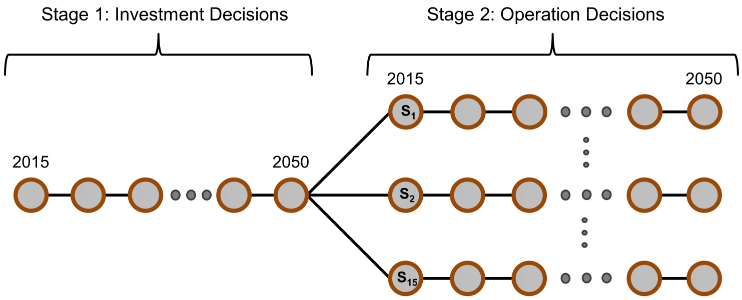

Figure 2.6: Illustration of a two-stage stochastic model with fifteen operational scenarios (adapted from [64])

2.3.1 Scenario generation

In stochastic programming, the scenario tree with its scenarios represents the true distribution of the uncertain parameters. Since it is computationally unrealistic to represent the entire distribution in a model, a subset of scenarios is often used. This also means that the optimal solution is estimated and not inherently found, and could therefore deviate from the exact solution. It is thus important that the set of scenarios gives a sufficient representation of the uncertain parameters, as inadequate scenarios can give inadequate model results and inaccuracies. Additionally, it is also important that the scenarios capture the dependency between various uncertain parameters, geographical regions and also dependencies in time [74].

Scenario generation methods are used in order to ensure that proper scenarios are chosen. These rely on data that describe the uncertain parameters, which could be a continuous probability distribution or a discrete dataset based on e.g. historical observations or simulations [74]. Several techniques are used in the literature, including random sampling, distance measures and moment matching [75–77]. In paper II and III of this thesis, a combination of random sampling and moment matching is used. This technique involves:

1. The uncertain parameters are described by long datasets spanning multiple years and with hourly resolution (e.g. wind and solar generation). From these datasets, historical days are sampled in order to construct a set of independent scenarios to make up the scenario tree. By sampling consecutive hourly values throughout a day, consistent daily correlations are captured. In addition, correlations between the three uncertain parameters are captured by sampling concurrent days, and spatial correlation is ensured by sampling the same day for each region.

2. Repeating this procedure multiple times in order to generate a large amount of possible scenario sets.

3. Calculating mean, variance, skewness and kurtosis (the first four moments) for the historic data and for each of the scenario sets.

4. Calculating the deviation of the moments of each scenario set to the historical

datasets, and then selecting the set of scenarios with the lowest deviation (best fit with the statistical properties of the original datasets).

The deviation of moments is calculated by:

$$d^{u,p,s} = \sum_{v=1}^{4} \sum_{t=1}^{T} abs[\frac{m_{hist}^{p,v,s,t} - m_{scen}^{p,v,s,t}}{m_{hist}^{p,v,s,t}}] \tag{2.5}$$

Where u is a given set of scenarios, p is the stochastic parameter (e.g. wind or solar), s is the season, v is the moment (m) order and t is the time-step. For all scenario sets U, the total deviation (d) for each scenario set across the stochastic parameters (p) and seasons (s) is found (P is the total number of stochastic parameters being modelled):

$$d^{u} = \sum_{p=1}^{P} \sum_{s=1}^{4} d^{u,p,s} \tag{2.6}$$

Then the set of scenarios with the lowest deviation d^{u*} among the large amount of sampled scenarios (U) is found, and used as input to the model.

$$d^{u*} = min(d^1, d^2, \ldots, d^U) \tag{2.7}$$

2.3.2 Solution quality

It is often desirable to reduce the number of scenarios in a stochastic model due to computational requirements, but this could give model results that depend on the scenarios rather than the underlying data. It is therefore important to evaluate the quality of the obtained solution and its stability [78]. In order to test if the model solution is stable with a given number of scenarios, one could test the in-sample stability of the model [79]. In-sample stability involves testing if solving the stochastic model gives approximately the same objective function value when using different scenario trees all based on the same underlying data and scenario generation method. This also includes assessing whether the value of the objective function is stable when increasing the number of scenarios. However, increasing the number of scenarios is challenging, as it quickly leads to very high computational requirements.

This problem is avoided when testing the out-of-sample stability [79]. This test investigates whether the obtained solution is stable when it is applied to the actual expected performance of the solution [80]. Here, the first-stage solutions from a stochastic model is fixed, and then run with a large number of scenarios representing the true distribution of the uncertain parameters. Since the first-stage solution is fixed, this does not lead to very high computational demands, as one could simply split the model up into several sub-models with a manageable scenario size. As an example, Seljom & Tomasgard test out-of-sample stability in [63]. Here, they estimate the optimal value using a stochastic model with 90 scenarios, fix the first-stage solution, and test it for 9 sub-models with different scenario trees. Since the investment decisions are fixed, this is equivalent to testing the model with 9·90=810 stochastic scenarios. They find that the objective value does not deviate much, and conclude that the solution is satisfactory.

There are also methods to evaluate the stochastic modelling approach relative to a deterministic one. By applying a test called the Value of Stochastic Solution (VSS), one can expose the energy system configuration from a deterministic model to the same short-term uncertainty as in a stochastic model [81]. It works by taking the investments from the deterministic model, implement them in the stochastic version, and then run it with the stochastic scenarios without allowing new investments. This will provide a measure of the value of following a stochastic investment strategy relative to a deterministic one [63, 81]. If the suite of technologies from the deterministic model is not able to meet the demand in all stochastic scenarios, it leads to infeasible solutions.

2.4 Alternative methods for dealing with short-term variability

While stochastic modelling techniques applied to long-term energy system models is the main focus of this thesis, other methods to deal with the short-term variability of solar and wind have been proposed in the literature. Several of these methods are reviewed by Collins et al. [23], including soft-linking long-term energy models with operational power system models, increasing or improving the temporal resolution and improving the technical representation (See Table 2.1 for a comparison).

Soft-linking involves coupling energy system models/IAMs to more detailed operational power system models, where characteristics of the power system obtained from the energy system model/IAM are used as input to the operational model. This allows a more detailed modelling of the operational aspects of the power system, particularly useful to get a better understating of the operational impacts of solar and wind generation. This approach is followed in Deane et al. [26], where a TIMES model of the Irish energy system is coupled to the PLEXOS power systems tool. They find that without important technical constraints, the energy system model can underestimate flexibility, underestimate wind curtailment and overestimate the use of base-load plants. Here, a uni-directional approach is followed, meaning that the operational power system model is only used to evaluate the outcome of the energy system model. Alternatively, a bi-directional approach could be followed, where the outcome of the operational power system model feeds back to the energy system model (see e.g. [82]). Finally, one could also hard-link two models to get one integrated model [83, 84].

A second approach is to improve the temporal representation in long-term energy models. This could be done by increasing the number of time-slices in a model, by for example including more representative days [85, 86]. Various methods for the selection of representative days have also been assessed, including e.g. heuristic methods, random sampling, clustering or even optimisation methods [43, 87–91]. Pfenninger tested several of these methods (downsamplng, heuristics and clustering techniques) using the open-source modelling framework Calliope [92].

Finally, one could also improve the technical representation in long-term energy models by adding operational constraints, which specifies e.g. ramp-rates, minimum load levels, kinetic inertia etc. [27, 93, 94]. Even though it is important to address the technical detail in a long-term energy system model, it has been shown that for high shares of variable renewable energy, the temporal resolution is more important [26].

Table 2.1: Strengths and weaknesses of various modelling approaches (adapted from [23])

Method	Strengths	Drawbacks
Stochastic modelling	Improved VRES representation, can improve optimality	Increased computational complexity
	Determines the need for back-up capacity endogenously	Requires complex scenario tree generation
	Considers uncertainty of parameters (e.g. VRES supply)	Can be difficult to implement
	Correlation between time-series can be accounted for	Should test stability and quality of solution
	Chronology can be captured (important for e.g. storage technologies)	
Soft-linking	More accurate modelling of systems operations	Need an additional power systems operational model
	Improved solution optimality (bi-directional)	No improved solution optimality (uni-directional)
	Allows assessment of power system reliability.	Optimality and convergence not guaranteed (bi-directional)
	Can be used to check results from energy system model	Need of harmonising model input
Temporal representation	Can be easy to implement	Difficult to assess short-term reliability of the power system
	Can improve optimality	Higher number of time-slices increases computational complexity
	Algorithms can give better selection of representative days (allowing fewer time-slices)	Improved selection of representative days requires complex algorithms
	Can capture correlation between time-series	Additional constraints needed to ensure back-up capacity
Technical representation	Can be easy to implement	Requires calibration using more detailed models
	Can improve optimality	Validity can not be guaranteed
	Can be combined with a low level of temporal detail	
	Only minor increase in computational demand	

Chapter 3

Models and data

This section gives a brief overview of the two models that were developed and applied in this thesis, and their most important input data. In addition, results from an additional example scenario of a 100% renewable European power sector is presented in order to demonstrate how this modelling tool can be used in further scenario analyses. More detailed descriptions of the models are presented in the supplementary materials for Paper II and III, in Appendix A and B respectively.

3.1 TIMES-Longyearbyen

The stochastic long-term energy system model TIMES-Longyearbyen consists of the single isolated region of Longyearbyen. Longyearbyen is situated on Svalbard, barely a thousand kilometres from the North Pole and has around 2000 permanent residents [95]. The settlement was founded in 1905 for coal mining purposes and is still supplied by Norway's only coal-fired power plant.

Using 2015 as the base-year, the model makes endogenous investments and operations in the power and district heat systems of Longyearbyen towards 2050. The discount rate in the base case is set to 4%, and the currency is Norwegian kroner (NOK). Investment decisions are made every 5th year, with sub-annual operations represented through 192 time-slices. In addition, the stochastic approach takes into account 60 different operational scenarios that can occur, where investments decisions are common for all 60 scenarios, but operational decisions are scenario dependent.

3.1.1 Input data

The current energy system composition in Longyearbyen and its calibration is an important input to the model, as it provides the starting point for the transition to a low carbon energy system and a basis for future investment needs. Today, the energy system in Longyearbyen consists of the coal-fired power plant as the main generator of electricity and heat, in addition to diesel generators and oil boilers for reserve and

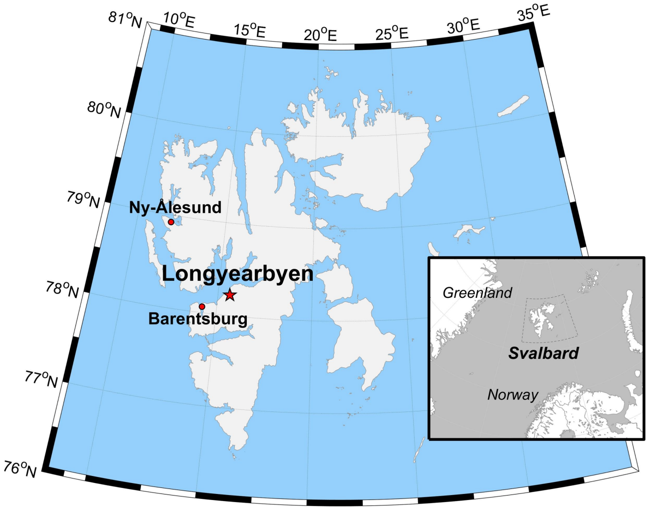

Figure 3.1: Map of Svalbard and its surroundings [56]

peak generation [96, 97]. There is also a very small amount of solar PV installed, both on the airport and on residential buildings [98]. In total, the energy system provides about 40 GWh electricity and 70 GWh heat annually (see monthly generation in Figure 3.2).

While the base-year relies on available statistics [99], assumptions have to be made for its future evolution. In the base case of TIMES-Longyearbyen, a significant decrease in energy usage is predicted for both electricity and heat. This is due to a huge potential for energy savings, particularly for heating. For electricity, the decline is associated with the closing of the coal mining operations as well as the coal-fired power plant, which today make up $\sim$30% of electricity consumption. Due to the uncertain development of the settlement, the sensitivity of the results on the demand projections is assessed. The results show that increased demand has a large impact on system size and costs, but a small impact on its composition.

How the demand profiles for electricity and heat are distributed within a year are also important inputs. This is represented through real data from the power plant in Longyearbyen, given on an hourly basis for 2017 and 2018 [99]. These datasets constitute the basis for the deterministic and stochastic profiles used in the model.

Technology costs (e.g. investment and O&M costs) are mainly retrieved from the Norwegian Water Resources and Energy Directorate [100]. The reasoning behind this is to use costs that are state-of-art as well as relevant in a Norwegian context.

Solar and wind data are based on Renewables.ninja[1], an online tool that allows users to simulate power output from solar panels and wind turbines anywhere in the world. The tool uses meteorological data from the MERRA reanalysis [101] to produce generation data for solar PV and wind through two models, the GSEE model (Global Solar Energy Estimator) [83] and the VWF model (Virtual Wind Farm) [102]. A high

[1] www.renewables.ninja

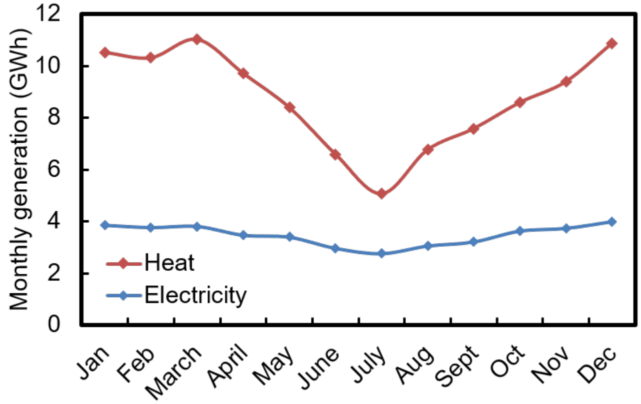

Figure 3.2: Monthly generation of electricity and heat in Longyearbyen in 2016 [99]

correlation (0.77) is found when comparing the wind speed data from Renewables.ninja to observations from the Norwegian Meteorological Institute [103] (see Figure 3.3). The mean wind speed in the observations are a bit higher than in the reanalysis (5.7 vs 4.4 m/s), indicating that the generation data based on the reanalysis should be considered conservative.

The maximum potential for onshore- and offshore wind turbines as well as ground-mounted solar PV are unconstrained in the model due to large available area. Residential solar panels are, on the other hand, constrained by the available roof area in the settlement [104].

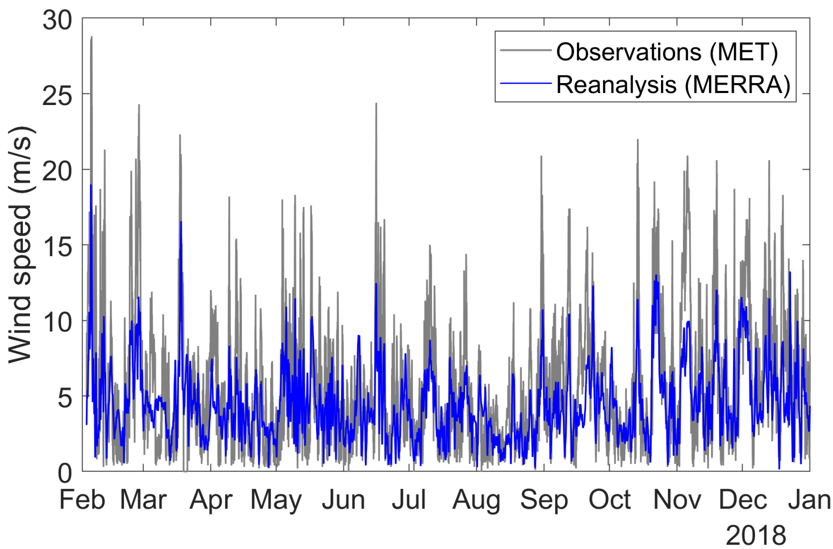

Figure 3.3: Comparison of wind speed data from renewables.ninja (reanalysis) and observations

3.2 TIMES-Europe

TIMES-Europe focuses on the European power and district heating systems. It covers 29 regions/countries in Europe, including the EU-28 countries plus Norway and Switzerland, with the exception of Cyprus and Iceland as they presently are not connected to the European power system.

Again, the base-year is set to 2015 with a horizon of 2050. The currency is ^{2015}€, the discount rate is 4%, and the model is run with investment periods of ten years. In Paper III of this thesis, different versions of this model with varying temporal resolution were used, all based on the same input data. This includes versions with respectively 12, 48, 192, 672 and 2016 time slices per year. Both stochastic and deterministic versions were developed.

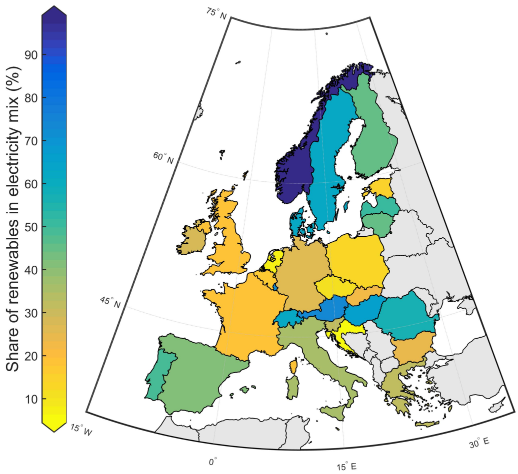

Figure 3.4: Map of included countries and their share of renewables in the power mix in 2015

3.2.1 Input data

The energy system characteristics of the base-year has been calibrated using available statistics from 2015, and is primarily based on data from the European Network of Transmission System Operators for Electricity (ENTSO-E) [105]. The electricity generation in Europe in 2015 consisted of ∼40% fossil fuels, ∼27% nuclear and ∼33% renewable energy. Figure 3.5 shows a comparison of the aggregated installed capacity in the base-year.

Projections of future electricity and heat demand are based on the EU reference case from 2016 [49]. This projection predicts that electricity demand will increase by 27% between 2015 and 2050 (∼3000 TWh to ∼3800 TWh), whereas the district heat demand increases by 10% (∼610 TWh to ∼670 TWh). Electrification of e.g.

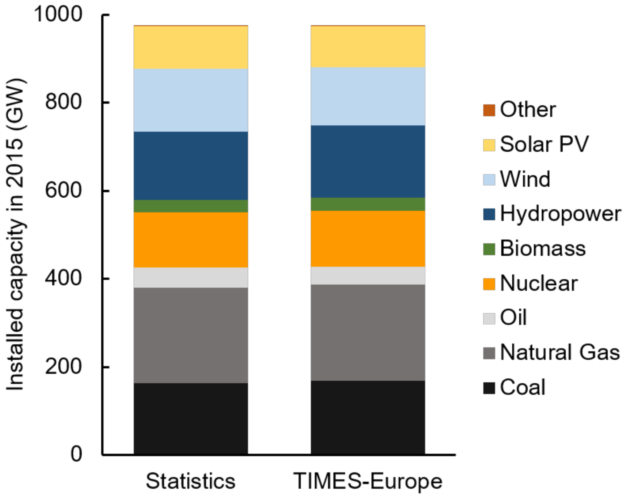

Figure 3.5: Calibration of installed capacity in the base year

vehicles could lead to a steeper increase of electricity demand than what is assumed here [106–108]. The impact of other demand projections could easily be tested by this new modelling tool.

The hourly electricity data is based on real data for all countries in the model, retrieved from ENTSO-E [109]. Six years of data are used, between 2010 and 2015, and make up the basis for both the deterministic and stochastic load profiles in TIMES-Europe. The model used in this thesis assumes that the shape of the load profile will remain the same also in 2050. However, measures such as increased electrification and demand side management will likely affect the future load curve. It would be interesting to assess the effect of a changing variability in the load curve on the results. The load curve for district heating is based on data from the model EnergyPlan [110].

Numerous technologies are available for investment, including conventional and renewable generation capacity, energy storage (e.g. batteries and hydrogen) and international transmission between pairs of countries. Costs are mainly drawn from publications from the European Commission [7, 111, 112].

Figure 3.6 shows the assumed evolution for the levelised cost of electricity (LCOE) of solar PV, onshore- and offshore wind in Europe towards 2050. LCOE is a measure of the discounted cost of producing electricity over the entire expected lifetime of the technology (€/MWh), using investment- and O&M costs as well as electricity generation data as input. These LCOE calculations are based on inputs to the TIMES-Europe model used in Paper III of this thesis. With three cost classes and different resource potential in each country, the LCOE varies widely across Europe in this model (Figure 3.6). One can see that solar PV and offshore wind have the steepest cost projections, whereas onshore wind is already a relatively mature technology. From these assumptions, solar PV becomes the cheapest power generation method in many regions in Europe by 2050, and one can also see that the cost of offshore wind approaches and even goes below that of onshore wind in some regions.

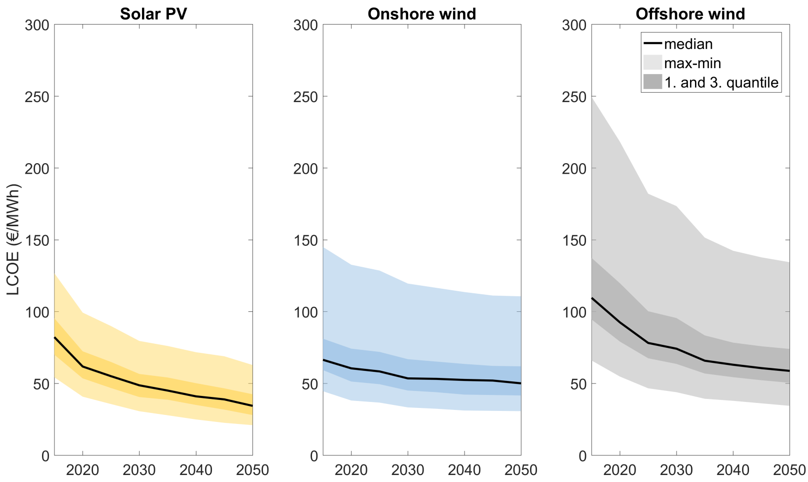

Figure 3.6: Simple LCOE projection used in TIMES-Europe

30 years of hourly solar and wind data between 1985 to 2015 are used, retrieved from Renewables.ninja. In contrast to the data retrieved for Longyearbyen, the per country data have been validated and bias-corrected using real generation data [83, 102]. There are large geographical differences in the solar and wind resource across Europe, which are important to capture in the model. Simultaneously, capturing the temporal differences are also important. A future highly interconnected Europe could both benefit from the smoothing effect seen when aggregating solar and wind generation over large areas, but it could also suffer from long-lasting continental-wide weather patterns. Maximum capacities for renewable energy technologies are used as an input to TIMES-Europe in order to limit the maximum installed capacities of a certain technology in a given country based on technical, environmental or political constraints [113–115].

3.2.2 A 100 % renewable European power system

As an additional exercise, and to demonstrate how TIMES-Europe can be used in further scenario analyses, it was run for a scenario leading to a 100 % renewable Europe in 2050. While the feasibility of 100% renewable energy systems have been debated [116, 117], there is a growing body of literature suggesting that a system driven entirely by renewable energy sources is both technically feasible and economically viable [19, 107, 118–120]. Bogdanov et al. [10] modelled the transition to a 100% renewable global power sector in 2050, achieving a technically feasible system with a levelised cost of electricity (LCOE) ∼25% lower than today. Solar PV was shown to become the dominant electricity producer (78 % of capacity in 2050), with battery storage also playing an integral part. In a similar fashion, Jacobson et al. [17] developed a roadmap for how 139 countries could use only renewables to cover all energy needs in 2050. By not only covering the power sector, Jacobson et al. also suggested how other sectors such as transport and industry could transition through e.g. electrification or the use of hydrogen.

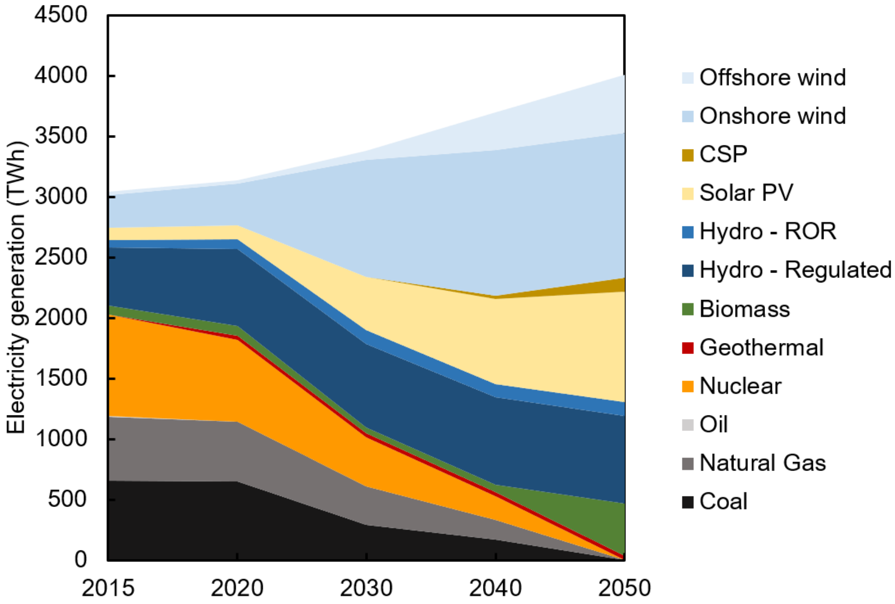

Figure 3.7: Electricity generation mix in a 100% renewable European power system scenario

The model set-up and assumptions in this 100% renewable energy scenario were identical to that of Paper III, but with an explicit constraint that CO_2 emissions must reach zero by 2050 and without investments in nuclear power capacity.

Figure 3.7 shows how the generation mix of electricity changes from today until 2050 in the 100% renewable scenario. Here, solar and wind dominate the electricity generation, with variable renewables being responsible for 67%. In order to maintain flexibility in the system, the model invests in large biomass capacities, energy storage as well as cross-country interconnection cables. There is also a high amount of offshore wind capacity, which helps diversifying the set of technologies, thus reducing the impact of their variability.

As expected, these results are similar to those found in Paper III. In that case-study, there were no constraints on emissions, but a conservative CO_2 tax was included. The share of renewables turned out to be 85% in 2050, where 60% was from variable renewables. Instead of large biomass capacities, much of the flexibility was provided by natural gas and nuclear capacity. In addition, interconnection capacity in 2050 was about 25% lower than in the 100% renewables scenario, but on the other hand the battery storage capacity was 20% higher. This is probably due to the extra biomass capacity in the 100% renewables scenario, which gives additional short-term flexibility and removes some of the need for batteries.

In terms of costs, a 100% renewables scenario turns out to have only 7% higher average annual costs than the case-study in Paper III. This is shown in Figure 3.8, which shows that a transition to a 100% renewable power system is not only technically feasible with the resources available, but would also be only slightly more expensive than a cost-optimal energy system.

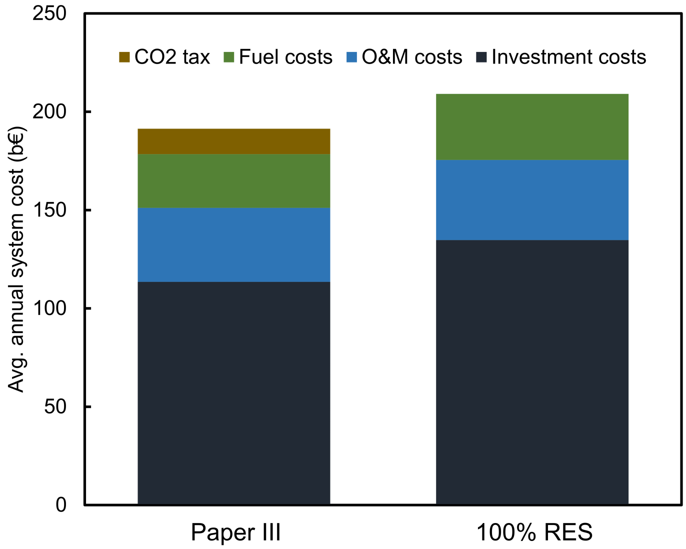

Figure 3.8: Comparison of annual costs in 2050 in the cost optimal and 100 % renewable Europe

The results of our 100% renewables scenario are supported by findings found in the literature [9, 121, 122]. As an example, the results are similar to those found in the Area scenario of Child et al. [16] in a study of a 100% renewable Europe. Here, they use the LUT transition model, a deterministic power system model with high spatial and temporal resolution (8760 time-steps per year). The composition of their system in 2050 is similar, with solar and wind supplied by hydropower and biomass dominating electricity generation. They find that variable renewables make up an even higher share of the electricity mix, with almost 80% of generation in 2050. In addition, their grid expansions are of similar order (fourfold increase versus a 3.4 times increase), while storage is much higher, likely due to effects of their modelling of prosumers. In terms of costs, Child et al. estimate annual costs of 276 b€/y, compared to 211 b€/y in our scenario. Here, it must be noted that the electricity demand in 2050 is about 25% higher in Child et al. than in our case (5000 TWh versus 4000 TWh), explaning the ∼30% difference in annual costs.

Chapter 4

Introduction to the papers

Paper I: **A review of modelling tools for energy and electricity systems with large shares of variable renewables**

Hans-Kristian Ringkjøb, Peter M Haugan and Ida Marie Solbrekke (2018),
Renewable and Sustainable Energy Reviews, 96, doi:10.1016/j.rser.2018.08.002

In this paper, we review 75 modelling tools, ranging from small-scale power system analysis tools to global long-term energy models. One of the main purposes of this paper is to give an updated overview of currently available modelling tools, their capabilities and to serve as an aid for modellers in their process of identifying and choosing an appropriate model. We present key information regarding their general logic, spatiotemporal resolution as well as technological and economic features. In order to include the most relevant and currently active tools, we only included models used in an academic publication after 2012. Additionally, to get the most updated and state-of-art information about the models as possible, our information was validated and updated through personal communication with developers or contact persons for 71 of the 75 reviewed models. While currently available modelling tools are able to assess most challenges of today's energy system, there are some challenges for future energy systems such as how to represent short-term variability in long-term studies, incorporate the effect of climate change and ensure openness and transparency in modelling studies.

Paper II: **Transitioning remote Arctic settlements to renewable energy systems - a modelling study of Longyearbyen, Svalbard**

Hans-Kristian Ringkjøb, Peter M Haugan and Astrid Nybø (2020),
Applied Energy, 258 doi:10.1016/j.apenergy.2019.114079

Norway's only coal-fired power plant is located in the Arctic settlement of Longyearbyen, Svalbard. Due to an ageing energy-infrastructure, a deteriorating coal reserve and questions about sustainability, Longyearbyen is in need of a new energy system. Through developing and applying a stochastic TIMES long-term energy model, we analyse and optimise an affordable and reliable future supply of electricity and heat primarily based on renewable energy sources in Longyearbyen. Our findings underline the importance of treating solar and wind variability in long-term energy models, especially for an Arctic case where energy security and reliability is crucial. Furthermore, we show that transitioning to an energy system based on renewables is found feasible, reliable and affordable. We recommend a solution based mainly on renewable power generation, but also including energy storage, import of hydrogen and adequate back-up capacity is considered when planning the future of remote Arctic settlements.

Paper III: **Short-term solar and wind variability in long-term energy system models - a European case study**

Hans-Kristian Ringkjøb, Peter M Haugan, Pernille Seljom, Arne Lind, Fabian Wagner and Sennai Mesfun, Submitted to Energy, December 2019

When solar and wind make up a large share of the power mix, it becomes increasingly important for long-term energy models to adequately represent their short-term variability. In this work, we use a long-term TIMES model of the European power and district heat sectors towards 2050 to explore how stochastic modelling of short-term solar and wind variability as well as different temporal resolutions influence the model performance. In comparison to a stochastic model version, our results show that deterministic models with low temporal resolution overestimate the contribution of variable renewables, leading to lower CO_2 emissions, a lack of system flexibility and an underestimation of associated costs. The deterministic models are only able to approximately reproduce the results of the stochastic model when the temporal resolution is significantly increased, but still lacking investment in system flexibility and with significantly longer solution times. Based on our findings, we therefore recommend that a stochastic approach is used in long-term studies of energy systems with large shares of variable renewable energy sources.

Chapter 5

Perspectives and outlook

The main research objective of this thesis was to contribute to a more robust modelling of solar and wind power in long-term energy system models, and by extension gain a better understanding of how variable renewables can be integrated into future low carbon energy systems. Due to the urgency of transitioning to a more sustainable energy system, this is a hot research topic at the moment, involving both methodological and policy-relevant questions.

Integrating variable renewables leads to a multitude of challenges on a range of timescales. This thesis gives an overview of these challenges, and the modelling tools currently available to assess them. The key properties and capabilities of 75 modelling tools are reviewed (Paper I), summarizing the state-of-art in energy modelling tools, and serves as an aid for new modellers in their search for a suitable model for their purposes. The findings of this review show that the currently available modelling suite is capable of investigating most challenges of today's energy system, but for a future with an increasing share of variable renewables some challenges remain.

One of the main challenges remaining for the modelling community is how to adequately represent short-term variability in long-term energy system models [123]. Misrepresenting this variability could lead to an overestimation of the penetration and contribution of variable renewables, which in turn could lead to underestimated costs, emissions and need for system flexibility [25].

This methodological challenge is assessed through two specific case studies in this thesis (Paper II and III). In a case study of a remote isolated Arctic settlement (Paper II), following a stochastic modelling approach gives investments in a system configuration able to meet the demand of heat and electricity through sixty different operational scenarios, including some with unfavourable wind and solar conditions. This ensures system robustness and security of supply, which is critical in the harsh climate of an isolated Arctic settlement. Traditionally, long-term energy system models have mainly been used for larger energy systems, but this paper shows that through applying a stochastic approach such models could also be used to study small isolated energy systems. This could have wide applications, not only for other Arctic settlements, but also for isolated island states at southern latitudes that despite a vastly different climate experience many of the same issues as communities in the Arctic.

In addition, this case-study also shows how Longyearbyen could transition from being supplied by coal into a low carbon settlement powered by renewable energy. The results indicate that a solution consisting of renewable power generation, energy storage, import of hydrogen and adequate back-up capacity is recommended to be taken into consideration by policy makers when planning the future of remote Arctic settlements. While some specifics are expected to vary with location, the major building blocks of the emerging system including wind, solar and hydrogen storage is applicable to other Arctic settlements. A sustainable energy supply to Longyearbyen could be a test bed for renewable solutions in the Arctic, relevant for other communities and an example for others to follow.

The usefulness of a stochastic approach versus a deterministic approach is further investigated in a case-study of the European power and district heat systems (Paper III). This is a much larger system than the settlement assessed in Paper II, with completely different dynamics and higher complexity. Due to ambitious targets for decarbonising the European energy system, this is also a highly relevant and interesting case-study.

While much work has been focused on the temporal resolution in long-term energy system models [23–25], Paper III is believed to be the first to explicitly compare stochastic models to deterministic models with increasing temporal resolution on the European scale. The findings show that a stochastic model is preferred in studies of energy systems with high shares of variable renewables. This is true also when increasing the temporal resolution of the deterministic models. Our results show that when the resolution is increased, the results from the deterministic models converge towards those of the stochastic model. However, this is achieved at much longer computational times, and the flexibility is still underestimated. Added heuristics that limit the contribution of variable renewables is needed in order to secure enough flexibility, but this leads to a 6% higher system cost than the stochastic case.

Our European case-study also shows that a large share of renewable electricity generation is the most-preferred pathway for the European power and district heat systems, even without imposing CO_2 constraints. Renewable electricity generation is already, and to an increasing extent will be, competitive with fossil fuelled power generation in many locations. Additional scenarios, such as the 100% scenario presented in this thesis, would be useful to further assess the policy-outcomes of the European decarbonisation.

This thesis demonstrates that the choice of temporal resolution and modelling approach plays an important role both for model results and insights as well as computational performance of long-term energy models, and should be carefully evaluated when such models are used for decision-making. When modelling energy systems consisting of large shares of variable renewable energy sources, a stochastic modelling approach is recommended, both due to its accuracy and also its computational efficiency in comparison to conventional deterministic models.

5.1 Future research

This thesis opens up several future research possibilities, partly to address limitations and shortcomings of the methods used and partly to explore expanded research and policy questions.

First, our findings suggest that a stochastic model approach should be used instead of deterministic models in cases with high shares of variable renewables. However, there are several methods for a more elaborate choice of time-slices used in deterministic models based on e.g. heuristics, optimisation or random sampling. These techniques could improve the low-resolution deterministic models, potentially to the extent that they become competitive with the stochastic modelling.

Second, the stochastic modelling approach followed in this study is only applied to power and district heating systems. The two models developed in this thesis could be expanded to encompass other energy sectors such as industry and transport. This would provide a better picture of the full system transformation that is required. It would likely lead to additional challenges, but coupling various sectors could also lead to positive effects that could ease the integration of variable renewables, e.g. by providing storage and/or flexible demand.

Third, the focus on the temporal resolution comes at the expense of a coarse spatial resolution. The European model developed for Paper III represents each country as one node, potentially missing the spatial effects and bottlenecks that could occur within a given country.

Finally, the developed models could be used to assess additional scenarios for the long-term development of energy systems. There are large uncertainties of the long-term evolution of technological developments and costs of different energy sources. Furthermore, many factors including costs depend on policy choices such as CO_2 taxes. Effects of alternative policies can be explored by comparative model runs. In addition, climate change may influence both energy demand and the resource potential of renewables in the future. Effects of climate change on regional resource potential should be taken into account in long-term energy modelling studies.

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Chapter 6

Scientific papers

Paper I

6.1 A review of modelling tools for energy and electricity systems with large shares of variable renewables

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A review of modelling tools for energy and electricity systems with large shares of variable renewables

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ABSTRACT

This paper presents a thorough review of 75 modelling tools currently used for analysing energy and electricity systems. Increased activity within model development in recent years has led to several new models and modelling capabilities, partly motivated by the need to better represent the integration of variable renewables. The purpose of this paper is to give an updated overview of currently available modelling tools, their capabilities and to serve as an aid for modellers in their process of identifying and choosing an appropriate model. A broad spectrum of modelling tools, ranging from small-scale power system analysis tools to global long-term energy models, has been assessed. Key information regarding the general logic, spatiotemporal resolution as well as the technological and economic features of the models is presented in three comprehensive tables. This information has been validated and updated by model developers or affiliated contact persons, and is state-of-the-art as of the submission date. With the available suite of modelling tools, most challenges of today's electricity system can be assessed. For a future with an increasing share of variable renewables and increasing electrification of the energy system, there are some challenges such as how to represent short-term variability in long-term studies, incorporate the effect of climate change and ensure openness and transparency in modelling studies.

1. Introduction

Electricity generation from renewable energy sources (RES) is increasing in Europe, much of it driven by ambitious targets for emission reductions set by the European Commission. In the 2050 Low Carbon Economy roadmap, the EU set a goal of reducing emissions to 80% below the 1990 level [1]. The EU also states that all sectors have to contribute to this reduction, but the sector with the highest potential for cutting emissions is the power sector. Through increasing the share of zero-emitting RES in the electricity mix, the power sector can almost totally eliminate its emissions by 2050.

Most of the increased RES in the electricity mix has in the latest years been, and is projected to be, solar and wind technologies. Part of this increase is due to the large cost reductions experienced and also projected. According to the International Renewable Energy Agency (IRENA), the levelised cost of electricity (LCOE) of solar photovoltaics (PV) has halved between 2010 and 2014 [2]. Furthermore, in November 2016, the winning bid to build the Danish offshore wind farm Kriegers Flak was as low as 49.9 €/MW h [3].

However, solar and wind are variable renewable energy sources (VRES) whose outputs vary temporally on many scales. This is especially the case for wind, which ranges from local gusts of only seconds to large scale patterns evolving over several years. The solar radiation is to some extent more predictable, where the daily and seasonal cycles are well known components. However, on shorter timescales the solar radiation can be difficult to predict due to the rapid change in cloud cover. In an electricity grid that requires a balance between generation and consumption, larger shares of VRES leads to multiple challenges.

On a very short timescale, from sub-seconds to minutes, challenges of VRES integration are related to the operation and management of the grid. The main issues include the reduction of inertia of the power system, the increase of curtailment events, the rate of change of frequency as well as the system reactive power capability [4]. Grid support services such as frequency and voltage regulation, fault ride through, spinning reserve and system restoration are currently provided by conventional technologies (i.e. mostly fossil fuelled power plants and hydropower). However, if solar and wind technologies are to replace much of the fossil fuelled capacities, they or new system components like batteries must be able to provide the required grid support services in order to maintain a stable and reliable grid. With existing technology, both wind turbines and PV systems are capable of providing grid support services, but limited to some drive-train topologies for wind turbines and generally only for large utility-scale PV systems [5–7].

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Table 1
List of models included in the review, their full name, who they are developed/published by, availability (AV), necessary software and references. Abbreviations used in the availability column: C – Commercial, D – Free demo version, F – Free, OS – Open-Source, AC – Free academic version, UN – Unknown (/not yet decided), ED – Free for educational purposes, UR – Upon Request.

Model	#	Full-name	Published/Developed by	AV	Software	Refs.
AURORAxmp	1	–	EPIS	C (D, A)	Stand-alone	[27,28]
BALMOREL	2	–	Hans Ravn	OS	GAMS + Solver	[29–31]
Calliope	3	–	ETH Zürich - Stefan Pfenninger	OS	Python	[32–34]
CASPOC	4	–	Simulation Research Netherlands	C (D)	Stand-alone	[35,36]
COMPETES	5	COmprehensive Market Power in Electricity Transmission and Energy Simulator	Energy Research Centre of the Netherlands	A[a]	AIMMS/GUROBI	[37,38]
COMPOSE	6	Compare Options for Sustainable Energy	Morten Blarke, ENERGIANALYSE.DK	A, C	Stand-alone[b]	[39–41]
CYME	7	–	CYME International	C (T)	Stand-alone	[42,43]
DER-CAM	8	Distributed Energy Resources Customer Adoption Model	Lawrence Berkeley National Laboratory	F	Online – None, Licensed – GAMS	[44–46]
DESSTinEE	9	Demand for Energy Services, Supply and Transmission in Europe	Imperial College London - Iain Staffell, Richard Green	OS	Excel/VBA	[47,48]
DIETER*	10	Dispatch and Investment Evaluation Tool with Endogenous Renewables	DIW Berlin - Alexander Zerrahn & Wolf-Peter Schill	OS	GAMS + Solver	[49,50]
DIgSILENT/PowerFactory	11	DIgital SImuLation of Electrical NeTworks - Power Factory	DigSilent GmbH	C	Stand-Alone	[51–53]
EMLab- Generation	12	Energy Modelling Laboratory - Generation	TU Delft - Richstein, Chappin, Bhagwat & de Vries	OS	JAVA & Maven	[54,55]
EMMA	13	The European Electricity Market Model	Neon Neue Energieökonomik GmbH - Lion Hirth	OS	GAMS/CPLEX	[56–58]
EMPIRE	14	European Model for Power system Investment with Renewable Energy	NTNU – Christian Skar et al.	UN	Xpress-Mosel	[59]
EMPS	15	EFI's Multi-Area Powermarket Simulator	SINTEF Energy Research	C	Stand-alone	[60–62]
EnergyPlan	16	–	Sustainable Energy Planning Research Group - Aalborg University	F	Stand-alone	[63–65]
energyPro	17	–	EMD International A/S	C	Stand-alone	[66–69]
Enertile[c]	18	–	Fraunhofer ISI	NA	Solver (CPLEX)	[70–72]
ENTIGRIS[d]	19	–	Fraunhofer ISE – Christoph Kost	NA	GAMS	[73,74]
ETM (1)	20	EUROfusion Times Model	EUROfusion	UN	GAMS/CPLEX, VEDA-FE & VEDA-BE	[75,76]
ETM (2)	21	Energy Transition Model	Quintel Intelligence	OS	Online tool	[77,78]
ETSAP-TIAM	22	The TIMES Integrated Assessment Model	ETSAP-IEA	F[e]	GAMS/CPLEX, Excel, VEDA-FE & VEDA-BE	[23,79]
EUCAD	23	European Unit Commitment and Dispatch	Univ. Grenoble Alpes – Jacques Després	NA	GAMS/CPLEX	[80,81]
EUPower-Dispatch	24	–	Carlo Brancucci Martinez-Anido (European Commission, JRC)	UN	GAMS/CPLEX (MATLAB)	[82–84]
ficus	25	–	TUM EI EWK – Dennis Atabay	OS	Python	[85–87]
GCAM	26	Global Change Assessment Model	PNNL	OS	BOOST, XERCES, JAVA, HECTOR	[88,89]
GEM-E3	27	General Equilibrium Model for Economy-Energy-Environment	European Commission Funded Multinational Collaboration	NA	GAMS (Solved with PATH)	[90–92]
GENESYS	28	Genetic Optimisation of a European Energy Supply System	RWTH-Aachen University – Alvarez, Bussar, Cai, Chen, Moraes Jr., Stöcker, Thien +	OS	Stand-alone	[93,94]
GridLAB-D	29	–	U.S Department of Energy	OS	Stand-alone	[95,96]
HOMER	30	Hybrid Optimisation of Multiple Energy Resources	NREL – Peter Lilienthal	C (T)	Stand-alone	[97–99]
HYPERSIM	31	–	Opal-RT	C	Stand-alone	[100–102]
iHOGA	32	Improved Hybrid Optimisation by Genetic Algorithms	Dr. Rodolfo Dufo-López - University of Zaragoza	ED (C) (pro +)	Stand-alone	[103,104]
IMAKUS	33	Iteratives Modell zur Ausbauplanung von Kraftwerken und Speichern	Technische Universität München - Philipp Kuhn	UN	MATLAB/CPLEX MATLAB/GUROBI	[105,106]
INVERT/EE-Lab	34	–	EEG - Vienna University of Technology	NA	Python	[107–109]
IPSA 2	35	Interactive Power System Analysis	IPSA Power	C	Stand-alone	[110,111]
IRiE	36	Integrated Regulating power market in Europe	NTNU (within a SINTEF project)	UR	AMPL - CPLEX/GUROBI & EMPS	[112–114]
LEAP	37	Long-range Energy Alternatives Planning	Stockholm Environment Institute	[f]	SA	[115,116]
LIBEMOD	38	LIBEralization MODel for the European Energy Markets	Frisch Centre & the Research Department at Statistics Norway	NA	GAMS	[117–119]
LIMES-EU	39	Long-term Investment Model for the Electricity Sector	Potsdam Institute for Climate Research - Paul Nahmmacher	UN	GAMS/CPLEX	[120–122]
LOADMATCH*	40	LOADMATCH Grid Integration Model	M. Z. Jacobson et al.	UN	UN	[123]
LUSYM	41	Leuven University System Modelling	K. Van den Bergh et al.	UR	GAMS (MATLAB)	[124]
MARKAL	42	MARKet ALlocation model	IEA-ETSAP	C (D)	GAMS + Solver (VEDA)	[125–127]

(*continued on next page*)

Table 1 (*continued*)

Model	#	Full-name	Published/Developed by	AV	Software	Refs.
MESSAGE	43	Model for Energy Supply Strategy Alternatives and their General Environmental Impact	IIASA	UR	GAMS & ORACLE	[128–130]
NEMO	44	National Electricity Market Optimiser	UNSW - Ben Elliston	OS	Python	[131,132]
NEMS	45	National Energy Modelling System	U.S. Energy Information Administration (EIA)	F[g]	[h]	[133,134]
Oemof (SOLPH)	46	Open Energy Modelling Framework	Oemof developing group (Reiner Lemoine Institut/ZNES Flensburg/OVGU)	OS	Python + Solver	[26,135]
OpenDSS	47	Open Distribution System Simulator	Electric Power Research Institute	OS	Stand-alone	[136–138]
OSeMOSYS	48	The Open Source Energy Modelling System	KTH - Howells et al.	OS	GNU MathProg	[139–142]
PLEXOS	49	PLEXOS Integrated Energy Model	Energy Exemplar - Glenn Drayton	C (A)	Stand-alone	[143–145]
POLES	50	Prospective Outlook on Long-term Energy Systems	CNRS (GAEL Energy), Enerdata, JRC-IPTS	NA	N.A.	[146–148]
PowerGAMA	51	Power Grid and Market Analysis	SINTEF Energy Research - Harald G. Svendsen	OS	Python	[149–151]
PRIMES*	52	Price-Induced Market Equilibrium System	E3MLab/ICCS at the Technical University of Athens	NA	–	[152–154]
ProdRisk	53	–	SINTEF Energy Research	NA	Fortran + COIN-CLP/CPLEX	[155–158]
PyPSA	54	Python for Power System Analysis	FIAS - Tom Brown et al.	OS	Python	[159–161]
RAPSim	55	Renewable Alternative Powersystems Simulation	NES, AUU - Pöchacker, Khatib, Elmenreich et al.	OS	Stand-alone	[162,163]
ReEDS	56	Regional Energy Deployment System	NREL	NA	GAMS (Excel & R)	[164–166]
ReMIND	57	Regional Model of Investments and Development	Potsdam Institute for Climate Impact Research	NA	GAMS/CONOPT	[167–169]
REMix	58	Renewable Energy Mix	DLR	NA	GAMS	[170,171]
renpass	59	Renewable Energy Pathways Simulation System	Frauke Wiese & Gesine Bökenkamp	OS	MySQL, R, RMySQL	[172,173]
RETScreen	60	The RETSCreen Clean Energy Project Analysis Software	Natural Resources Canada	F	Windows with .NET	[174,175]
SAM	61	System Advisor Model	U.S. Department of Energy and NREL	F	Stand-alone	[176–178]
SIMPOW	62	Simulation of Power Systems	Solvina	C (D)	Stand-alone	[179,180]
SIREN	63	"Sustainable Energy Now" Integrated Renewable Energy Network	Sustainable Energy Now Inc. - Angus King	OS	Stand-alone	[181,182]
SNOW[i]	64	Statistics Norway's World model	Statistics Norway	F	GAMS & MPSGE	[183–185]
stELMOD	65	Stochastic Electricity Market Model	Jan Abrell (ETH Zürich) & Friedrich Kunz (DIW Berlin)	OS	GAMS/CPLEX	[186–188]
SWITCH	66	Solar, Wind, Transmission, Conventional generation and Hydroelectricity	Fripp, Johnston & Maluenda	OS	Python	[189–191]
Temoa	67	Tools for Energy Model Optimisation and Analysis	NC State University - K. Hunter et al.	OS	Python + Solver	[192–194]
TIMES	68	The Integrated MARKAL-EFOM System	IEA-ETSAP	C (D)	GAMS + Solver (VEDA)	[195–197]
TIMES-Norway	69	As TIMES	IFE/NVE	[j]	GAMS, CPLEX/XPRESS	[24,198,199]
TIMES-Oslo	70	As TIMES	IFE	[k]	GAMS, CPLEX/XPRESS	[25]
TRNSYS18	71	TRaNsient SYstem Simulation	TESS, SEL, UW, CSTB, TRANSSOLAR	C (D)	Stand-alone	[200–203]
urbs	7372	–	TUM (Hamacher, Huber & Dorfner)	OS	Python (Solver)	[204,205]
WEM*	73	World Energy Model	International Energy Agency	NA	Vensim + others	[206–208]
WeSIM	74	Whole-electricity System Investment Model	Imperial College of London	NA	Unknown	[209,210]
WITCH	75	World Induced Technical Change Hybrid model	FEEM	UR	GAMS	[211–213]

[a] Own tool of ECN used for quantitative analysis for EU or national projects (it could also be freely used for research by academia with whom ECN cooperates).
[b] Good performance open-source MILP solver included (COINMP), commercial solver license recommended (e.g. CPLEX or GUROBI).
[c] Previously called PowerACE.
[d] Previously RESlion.
[e] Free of charge for Institutes appointed by one of the Contracting Partners of ETSAP.
[f] Free for students. Free for country government, NGO or academics in developing countries. Commercial for Academic, non-consulting and consulting in OECD countries.
[g] Excluding IHS Global Insight macro sub-model.
[h] Intel Fortran, Eviews, IHS Global Insight model, OML & Xpress solver, GAMS & Xpress, AIMMS & CPLEX, R, MS Windows OS.
[i] There is both a global version and a Norwegian version of the model (SNOW-NO).
[j] Not available (Except for cooperation with Ph.D. or master students).
[k] Not available (Except for cooperation with Ph.D. or master students).

On an hourly timescale, both wind turbines and photovoltaic systems can shift from generating at nominal power to not generating anything at all [8]. With a large VRES penetration, this can lead to challenging ramping situations, periods of oversupply as well as periods where the renewable sources are not able to meet the demand. Future power systems with high shares of VRES may require increased system flexibility through e.g. flexible power plants, energy storage, demand response and transmission grid extensions [8].

On longer timescales, challenges related to VRES integration include identifying pathways to a renewable and emission free energy system, assessing different scenarios and testing the effect of various policies. For example by assessing the impact of a carbon tax, the future evolution of electricity and fuel prices or how much the demand of energy is going to increase due to population growth and increased standard of living. Due to the long investment cycles in the energy sector, such analyses usually cover a time span of several decades [9]. Technological possibilities for more geographically distributed energy production and better control systems suggest that the development of energy production, storage and distribution systems in the near future may depend more on consumer or prosumer preferences and multi-level governance in addition to planning and optimisation on a national level. Business opportunities arising from periodically low electricity prices can stimulate new technologies and reduce curtailment. It is suggested that such factors may be relevant to include in scenario modelling.

From short-term operation to long-term energy system planning, many different models have been developed to assess the numerous challenges related to energy and electricity systems. Jebaraj and Iniyan [10] reviewed a spectrum of energy models, including energy planning models, supply-demand models, forecasting models, renewable energy models, emission reduction, optimisation and even emerging modelling techniques based on neural networks or fuzzy logic. Connolly et al. [11] looked at 37 models specific for the integration of renewables in energy systems. Their review also considered a large variety of modelling types, and was based on communication with the model developers through surveys. Sinha and Chandel [12] had a specific focus on modelling of hybrid renewable energy systems, mainly focused on stand-alone systems in urban, rural and remote areas. Pfenninger et al. [13] looked at how energy models face the challenges seen in today's system; resolving time and space, balancing uncertainty and transparency, addressing growing complexity and integrating human behaviour and social risks and opportunities. Moreover, Hall and Buckley [14] reviewed and categorised 22 energy models that are used in the United Kingdom. There are also several other reviews worth mentioning; Després et al. (2015), Mahmud and Town (2016), Hedenus and Johansson (2013), Foley et al. (2010), Bhattacharyya and Timilsina (2010) and Van Beuzekom et al. (2015) [15–20]. In addition, The International Energy Agency has published an extensive report on the use of energy models, scenarios and their assumptions [21].

There has been a high level of activity on model development in recent years, with many new models and modelling features appearing in the literature. This has partly been motivated by the need to better address the challenges of VRES integration. Many previous reviews are restricted to parts of the modelling landscape, e.g. modelling of the transport sector or local energy systems [12,16]. This review seeks to cover a wide range of aspects, extending previous reviews, and providing an updated overview of state of art modelling tools by the time of submission. The aim of the paper is to present an assortment of models that are capable to assess challenges faced in today's energy system, useful for modellers to identify suitable models for their purposes.

2. Materials and methods

2.1. Included models

In order to include only the most recent and currently active models, a criterion was set that each model must have been used in a publication after 2012. The starting point for identifying models was in previous review papers [10–20], but many of the models in these reviews have not been active since 2012 and are therefore excluded. Some of the models were found through the Open Energy Modelling Initiative [22], while the majority of models were identified via manual web searches based on keywords and citations.

As models are continuously developed and updated, this exercise is basically shooting at a moving target. Therefore, to ensure that the information provided in this paper is state of the art at the time of submission, it has been validated and updated through personal communication with developers or contact persons affiliated with the models. Out of the 75 models included in the review, 71 are validated. Table 1 presents the models included in the study, their developers, availability and the necessary software to run them. Missing replies are marked by asterisked entries in the "model" column, and might be due to wrong contact information.

It must be noted that this review does not explicitly distinguish between models and modelling tools. Some models are better regarded as tools or frameworks, where there is no data already in the model, but with equations and constraints from which a specific model can be built. Such tools are therefore usually highly flexible in the kind of systems they can model, where the user can define the spatiotemporal resolution, horizon, energy carriers, demand sectors etc. An example is the MARKAL/TIMES family of models, which have been applied to all from global to isolated island energy systems. In the tables these have been entered with their most typical characteristics. Specific examples of models developed by the TIMES modelling framework by adding ETSAP-TIAM, TIMES-Norway and TIMES-Oslo [23–25] are also included. OEMOF is another such framework [26]. It consists of a toolbox where several energy system modelling approaches can be integrated as single libraries. These libraries can then be used in so-called applications to build a computable model. In this review the application of a library called SOLPH has been used to illustrate OEMOF's capabilities.

2.2. Model features and properties

The model categorisation has been structured following the overarching typology presented by Després et al. [15]. This consists of the general logic, the spatiotemporal resolution as well as the technological and economic parameters of the models. Fig. 1 presents an overview of this categorisation, with a simplified flowchart that aims to aid prospective modellers in identifying an adequate modelling tool for their needs.

Starting with the problem statement at hand, the reader can find comprehensive information about the capabilities of the included models in Tables 1–3. Table 1 introduces the reviewed models alongside information about their availability, software requirements and developers. The general logic and spatiotemporal resolution is presented in Table 2, whereas Table 3 contains information about technological and economic parameters. By assessing the information stored in these tables, the reader should be able to identify and choose a model capable of giving insights to their specific question, model the involved processes with an adequate spatiotemporal resolution, and possess the necessary technological and economic properties.

The next paragraphs explain the various categories in further detail.

2.2.1. General logic

2.2.1.1. Purpose. Energy and electricity models are usually developed to solve a problem or to answer a given question. Four different purposes are identified. Models can fit into several of these categories:

Power System Analysis Tools – Tools developed to study power systems with a high degree of detail, usually dealing with power flows, fault level studies, dynamic stability etc. A typical application can be to study the power electronics in a wind turbine connected to the grid.

Operation Decision Support – Tools developed to optimise the

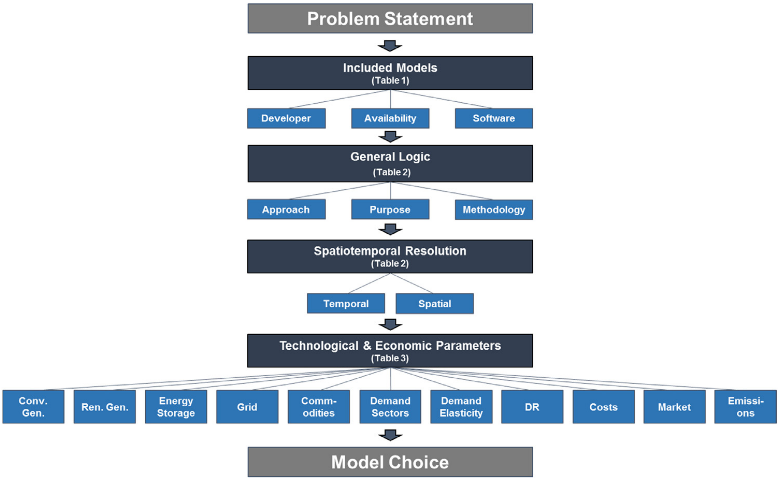

Fig. 1. Flowchart illustrating the model categorisation followed in this paper, where this information can be found, and how it can be applied in a process to identify a specific model for a given use. The abbreviations Conv. Gen. and Ren. Gen. refer to conventional and renewable generation technologies, and DR refers to demand response.

operation/dispatch of the energy/electricity system, considering for example unit commitment. Such models operate on short-term timescales, but on a larger scale than power system analysis tools e.g. on a national or European scale.

Investment Decision Support – Tools that optimise the investments in the energy/electricity system. Due to the long investment cycles in the energy sector, such models are usually long-term models. Investment modelling can be done either with a **myopic** or a **perfect foresight** approach. With a perfect foresight approach, the system is optimised for the whole study-period simultaneously, with complete knowledge of how market parameters will evolve across the planning horizon [196]. For the myopic approach, investments are made sequentially, only based on information from the current investment period.

Scenario – Such tools investigate future long-term scenarios in the energy/electricity sector. They can for example be used to evaluate the impact of various policies.

2.2.1.2. Approach. Energy models generally follow two approaches; either a **top-down** or a **bottom-up** approach. Often referred to as the engineering approach, bottom-up models are based on detailed technological descriptions of the energy system. On the other hand, top-down models follow the economic approach, considering macroeconomic relationships and long-term changes [21].

In many cases, particularly when assessing the integration of variable renewables, both long-term changes and technological properties are of high importance. To capture both, models can be combined in **hybrid** approaches [214].

2.2.1.3. Methodology. The methodologies of energy and electricity models are generally divided into three main categories; simulation, optimisation or equilibrium models.

Simulation models simulate an energy-system based on specified equations and characteristics. They are often bottom-up models, with a detailed technological description of the energy system. Simulation models allow the testing of various system topologies, as well as impacts and developments of various scenarios. **Agent-based simulation** is a specific case of models where actors participating in e.g. the electricity market are modelled explicitly as agents with distinct strategies and behaviour.

Optimisation models optimise a given quantity. When modelling energy and electricity systems this quantity is usually related to the system operation or investment, while some models have the capability of optimising several aspects simultaneously. The majority of optimisation models use a **linear programming** (LP) approach, with an objective function which is either maximised or minimised (e.g. minimising the total system cost), subject to a set of constraints (e.g. balancing the supply and demand in the grid). **Mixed-integer linear programming** (MILP) forces certain variables to be integral, which can be useful when for example optimising how many power plants or the number of wind turbines one should invest in. Optimisation models can also be **non-linear,** i.e. the objective function or constraints are non-linear. **Heuristic optimisation** models differ from traditional optimisation modelling as they do not necessarily find the optimum solution [215]. By simple and fast methods, such as the Covariance Matrix Adaption Evolution Strategy (CMA-ES) [216], the optimal solution can be approximated.

Equilibrium models take an economic approach, modelling the energy sector as a part of the whole economy and studies how it relates to the rest of the economy. Such models are therefore often used to evaluate the impact of various policies on the economy as a whole. General equilibrium models, or **computable general equilibrium models** (CGE), consider the whole economy. They determine the equilibrium across all markets, and determine important economic parameters such as the gross domestic product (GDP) endogenously. **Partial equilibrium models** (PE) focus on balancing one market, in this case the energy or electricity market, with the rest of the economy not modelled.

2.2.2. Spatiotemporal resolution

The spatiotemporal resolution of a model is particularly important, as it sets limitations to which processes can be appropriately modelled. This is especially important in systems with a large share of VRES, as the variability of the solar and wind resources must be captured. This is further discussed in Section 4.1.

Time-steps can vary from milliseconds in power system analysis tools to several decades in long term economic equilibrium models. In some models time-steps are fixed, while in others the time-step is given by the input data. Likewise, the geographical scope can vary from analysing single projects or individual buildings to modelling the energy system of the whole world.

2.2.3. Technological and economic properties

Measures such as grid development, energy storage and demand side management have been identified as some of the key contributors for successfully building an energy system containing large shares of

VRES. When modelling the impact of increased shares of VRES in the European energy system, some properties and features of a model are therefore crucial. Model components and properties are categorized as follows:

Conventional Generation – Modelling of conventional generation technologies such as thermal generation, nuclear and bioenergy can be done in various ways, for example by modelling each power plant individually or by aggregating all power plants of a technology within a region.

Renewable Generation – Whereas conventional generation is dispatchable, renewable generation (except geothermal & tidal) depends on meteorological conditions. These conditions, and thus the generation, can be modelled by meteorological data (e.g. wind speed data in combination with a power curve for wind production), by stochastic methods (e.g. stochastic inflow modelling for hydropower scheduling) or not modelled at all (e.g. by deriving capacity factors from historical data). The renewable generation technologies considered are: wind, PV, solar thermal, concentrated solar power, hydropower with reservoir, run-of-the-river hydropower, geothermal energy, wave power and tidal energy.

Energy Storage – Due to the fluctuating output from solar and wind that does not necessarily comply well with the demand, means of storing energy is important. Pumped hydropower storage (PHS) is the only large-scale energy storage technology widely available today, and amounts about 96% of the storage capacity in Europe [217]. Due to limited available locations for further PHS expansions and increasing need for energy storage, other solutions such as hydrogen, thermal energy storages, batteries, or compressed air energy-storage (CAES) may be increasingly important in the future.

Grid – Power system analysis tools apply detailed modelling of power systems, including power flows, short-circuit analyses, harmonics, stability and so on. In models which mainly are concerned with load flow between regions, three approaches with decreasing complexity are followed. These are AC (alternating current) flow, DC (direct current) flow or by net transfer capacities (NTC).

Modelling a grid with N nodes using AC power flow results in 2N non-linear equations that must be solved iteratively for each time step [218]. Understandably, this is computationally demanding, and therefore in many cases a simplified linearised power flow is preferred (often referred to as DC-modelling). Studies have shown that the error of using the DC simplification is only in the order of a few percent, except at very high loadings [219,220]. At high loadings the reactive power consumption increases by the power of two, thus making the DC simplification less accurate as it does not represent reactive power. However, Brown et al. [219] limited the loading of their modelled power lines due to n-1 security and to allow for extra reactive power flows, thus avoiding this issue in all but a few instances (they allowed some overloading in order to avoid unnecessary grid expansions).

The NTC approach considers transfer capacities, often interregional exchange capacities between countries. Studies have shown that the NTC approach shows small differences compared to the linearised load flow [9]. Due to its simplicity and overall high accuracy, modelling with the NTC approach is highly popular and used in many of the models.

Commodities – Whilst many models have a specific focus on the power sector alone, some models also include other commodities. This can be beneficial, as various forms of energy can be able to complement each other (see Section 4.2). The focus is on commodities which are believed to be the most important for a 100% renewable energy system, namely electricity, heat and hydrogen. In addition all commodities related to fossil fuels have been classified simply as fuels without specifying which specific fuels are modelled.

Demand sectors – End-use sectors have been split in the building, industry and transport sectors. This means that commercial and residential buildings are combined in the building sector, and likewise agriculture is included in the industrial sector. Many models concerns only the electricity systems and uses an aggregated demand/load based on the consumption of electricity in all of the sectors combined.

Demand Elasticity – A measure of how the demand changes due to price fluctuations. E.g. the demand of electricity might decrease if the prices become higher.

Demand Side Management – Demand side management (DSM) concerns measures taken on the consumers' side of the energy system, including improvements in energy efficiency, energy conservation and demand response (DR) [23].

Demand Response (DR) is the procedure of shifting certain loads from hours when the demand is higher than the supply to hours with surplus generation. This helps balancing the fluctuating output from variable renewables, and is a good complement to energy storage. It also reduces the highest load peaks for which the electrical grid is designed, thus reducing the need of expensive grid-development. As an example, the charging of electric vehicles can be shifted from the peak in demand usually experienced in the afternoon to the night when the consumption is much lower.

In terms of modelling, DR can be treated as a negative storage, by "storing" the demand rather than excess energy. It can also be modelled by shifting unmet flexible loads (e.g. charging EVs) to following time-steps. A third possibility is to model DR as a negative generating unit, with associated maximum capacities, costs etc.

Costs – Although very difficult to model accurately, costs are crucial for the modelling results. Investment, operation & maintenance, fuel, CO_2, taxes and balancing costs (start-up, shut-down and ramping costs) are included in the model categorisation.

Market – Most of the models assessed treat the market by simply balancing supply and demand under perfect market conditions. However, some models have no market modelling at all, whilst other models can treat the spot market (merit-order modelling), the reserve market or even the balancing market.

Emissions – Some models include modelling of various greenhouse gases and pollutants such as CO_2, NO_x, SO_x or CH_4, often as a side product of generation from various fuel types. In some models, any pollutant can be modelled as its own commodity whereas some models treat greenhouse gas emissions by CO_2 equivalents.

3. Results

Table 1 presented the 75 models included in this review, their availability, developers and software requirements. In this section, Tables 2, 3 extends this information by presenting the specific capabilities of each of the models.

The general logic and the spatiotemporal resolution of the models are presented in Table 2. Most of the models are bottom-up optimisation models with the purpose of giving investment and/or operation decision support. Such models work on several timescales and modelling horizons, and can analyse small scale energy systems as well as systems on the scale of the whole of Europe. Thirteen power system analysis tools are included in this review, all of which are bottom-up simulation models. There are also some hybrid models and one pure top-down model. These are mainly long-term and large-scale models focusing on scenario analysis.

Fig. 2 illustrates the relationship between the geographical coverage and the temporal resolution of the reviewed models. Panel a) presents models with pure bottom-up and top-down approaches, whereas panel b) presents hybrid models. Each model has been assigned a model ID

Table 2
General logic and spatiotemporal resolution. Abbreviations used in the table: **Purpose:** IDS – Investment Decision Support, ODS – Operation Decision Support, S – Scenario, PSAT – Power System Analysis Tool, A – Analysis; Approach: BU – Bottom-up, TD – Top-down, H – Hybrid; **Methodology:** S – Simulation, LP – Linear Programming, MIP – Mixed Integer Programming, PE – Partial Equilibrium, A- Accounting, ABS – Agent-based Simulation, MIQCP – Mixed Integer Quadratically Constrained Programming, CGE – Computable General Equilibrium, E – Equilibrium, CMA-ES – Covariance Matrix Adaptation Evolution Strategy, HO – Heuristic Optimisation, ECE – Economic Computable Equilibrium, SDDP – Stochastic Dual Dynamic Programming; **Temporal Resolution/Modelling Horizon/Geographical Coverage:** UD – user-defined, NL – No limitations.

Models	#	Purpose	Appr.	Methodology	Temporal resolution	Modelling horizon	Geographical coverage
AURORAxmp	1	I & ODS, S, PSAT	BU	S, LP, MIP, PE	UD (Hourly)	UD (50+ years)	Single project → Global
BALMOREL	2	I & ODS	H	PE/LP (MIP)	Hourly/Aggregate	50 years (UD)	Regional → International
Calliope	3	I & ODS	BU	LP (MIP under development)	UD	UD	UD
CASPOC	4	PSAT	BU	S	UD	µs to 1 year	Single-System/Local
COMPETES	5	I & ODS	BU	LP (In.), MIP (Op.)	Hourly	UD	National (Europe)
COMPOSE	6	ODS & S	BU	A (In.), MIP(Op.)	UD (Usually hourly)	UD	Single-Project/System
CYME	7	PSAT	BU	S	UD (Usually ms)	UD	Single-System → Regional
DER-CAM	8	I & ODS	BU	MIP	Hourly (In.) & Minutes (Op.)	Up to 20 years	Single-Project → Regional
DESSTinEE	9	S, I & ODS	BU	S	Hourly	2050	National (Europe)
DIETER*	10	I & ODS	BU	LP	Hourly	1 year	Calibrated to Germany
DIgSILENT/ PowerFactory	11	PSAT	BU	S	UD	UD	Power Systems
EMLab-Generation	12	IDS	H	ABS	Yearly	2050	Two Markets/Countries
EMMA	13	I & ODS	BU	LP	Hourly	Long-term economic equilibrium	National (Europe)
EMPIRE	14	IDS	H	LP (Multi-horizon stochastic)	5 y (In.), UD time-slices per year (Op.)	Typically 40–50 y	National (Europe)
EMPS	15	I & ODS	BU	LP[a]	Weekly[b]	25 years	Regional → Continental
EnergyPlan	16	S, IDS	BU	S	Hourly	1 year	Local → Continental
energyPro	17	I & ODS	BU	AO[c]	Minutes	Max 40 years	Local → Regional
Enertile	18	I & ODS	BU	LP	Hourly	Usually 2050	EUMENA (National)
ENTIGRIS	19	I & ODS	BU	LP	Hourly (Op.), 5 y (In.)	2050	Regional → International
ETM (1)	20	S	BU	PE & LP	Six time slices: three seasons (winter, summer and intermediate), & day/ night	2100	Global (17 regions)
ETM (2)	21	S	H	S	15-min (+ Hourly & Yearly)	2050	Community → International
ETSAP-TIAM	22	I & ODS, S	BU	LP, PE	Yearly (seasons & day-night hours)	2100	Global (15 regions)
EUCAD	23	ODS	BU	MIQCP	Hourly	Yearly	National (Europe)
EUPower-Dispatch	24	ODS	BU	MIP	Hourly	Yearly	National (Europe)
ficus	25	I & ODS	BU	MIP	Typically 15 min	1 year	Local → National
GCAM	26	S	H	PE	5 years	2100	Global (Regional)
GEM-E3	27	S	TD	CGE	5 years	2030 and 2050	Global (38 regions)
GENESYS	28	IDS	BU	CMA-ES & HO	Hourly	2050	EUMENA (National)
GridLAB-D	29	PSAT	BU	ABS	Sub-seconds – Years	3–5 Years	Local → National
HOMER	30	I & ODS	BU	S & O	Minutes	Multi-Year	Local
HYPERSIM	31	PSAT	BU	S	10 µs	UD	Single-System → Regional
iHOGA	32	I & ODS	BU	HO	Hourly	Yearly	Local
IMAKUS	33	I & ODS	BU	LP	Hourly	Several decades	Germany
INVERT/EE-Lab	34	S	BU	S	Y (In), Monthly (Op)	2030/2050/2080	Buildings
IPSA 2	35	PSAT	BU	S	[d]	[e]	Power Systems
IRiE	36	ODS	BU	MIP	15-min	Yearly	26 areas in Northern Europe
LEAP	37	S	H	S & LP	Yearly	Usually 20–50 years	Local → Global
LIBEMOD	38	S	H	ECE	Yearly (El split in summer and winter season; one day split into day and night)	1 → 20 years	National (Europe)
LIMES-EU	39	S, I & ODS	H	LP	5/10 y (6 rep. days per year, 8 time slices per day)	2050	National (Europe)
LOADMATCH*	40	S	BU	S	30 s	6 years (2050–2055)	CONUS (4° × 5° WWS data)
LUSYM	41	ODS	BU	MIP	15 min/Hourly & Daily (UC)/Weekly (Scheduling)	Daily/Weekly (UC) & Yearly (Scheduling)	National
MARKAL	42	S	BU	LP/MIP, PE	Multiple years (UD time-slices within a year)	Long-term (UD)	Local → Regional
MESSAGE	43	S, IDS	H	LP	UD (Multiple years)	Long-term (50–100+ years)	Global (11 Regions)
NEMO	44	I & ODS	BU	CMA-ES & S	Hourly	Typically 1 year	National
NEMS	45	S	H	S, O, PE	Yearly	2050	Regional/National (U.S.)
Oemof (SOLPH)	46	S, I & ODS	All	LP, MILP, PE	Seconds to years	UD	UD
OpenDSS	47	PSAT	BU	S	UD (1 s to 1 h)	UD	Distribution feeders/areas
OSeMOSYS	48	IDS	BU	LP	UD (intra-annual)	UD (10–100 y)	Community → Continental
PLEXOS	49	I & ODS, S, PSAT	BU	[f]	UD up to 1 min (Usually hourly)	UD (1 day to 50 + years)	Single project→ Global
POLES	50	S, I & ODS	H	PE/S	Yearly (Sectoral load shape for two typical days with two-hour resolution)	2050 (2100)	Global (66 regions)
PowerGAMA	51	S (IDS)	BU	S, LP	Usually hourly	Usually 1 year	Regional/National

(*continued on next page*)

Table 2 (*continued*)

Models	#	Purpose	Appr.	Methodology	Temporal resolution	Modelling horizon	Geographical coverage
PRIMES*	52	S, IDS	H	PE	Yearly	Long-term	National (Europe)
ProdRisk	53	ODS	BU	LP (SDDP)	Usually 5–25 weekly periods	Usually 3–10 years	Local → National
PyPSA	54	I & ODS, PSAT	BU	LP	Hourly	1 year	Local → Continental
RAPSim	55	PSAT	BU	S	Minutes	Multiple days	Local
ReEDS	56	S (& IDS)	BU	LP & PE	[g]	2050	[h]
ReMIND	57	S	H	NLP	[i]	2150	Global (11 regions)
REMix	58	I & ODS	H	LP	Hourly	Typically 1 year	Regional (Germany) → National (Europe)
renpass	59	ODS, S	BU	S (In) & O (Op)	Typically Hourly	1 year	Regional/National (Western Europe)
RETScreen	60	IDS, S	H	S	Monthly/Yearly/Daily	Max 100 years	Single-system → Global
SAM	61	IDS	BU	S	Sub-Hourly	1 year (/Lifetime for e.g. batteries + PV)	Single system
SIMPOW	62	PSAT	BU	S	Milliseconds	Seconds	Single-system → Local
SIREN	63	S	BU	S	Hourly	1 year	Regional/National
SNOW	64	S	H	CGE	Yearly	UD (1–100 years)	[j]
stELMOD	65	ODS	BU	MIP	Hourly	1 year	National (Europe)
SWITCH	66	I & ODS	BU	MIP	Hourly Dispatch/Decadal Investment Period	UD (2050)	Regional/National[k]
Temoa	67	S	BU	LP	Yearly (With UD time-slices)	UD	Regional (UD)
TIMES	68	I & ODS	H/BU	LP/MIP, PE	Multiple years - with UD time-slices within a year	Long-term (UD)	Local - Global
TIMES-Norway	69	S, IDS (& ODS)	BU	LP	Multiple years – 260 time-slices per year	2050	Norway (Sweden optional)
TIMES-Oslo	70	S, IDS (& ODS)	BU	LP	Multiple years – 260 time-slices per year	2050	Oslo (Norway optional)
TRNSYS18	71	PSAT	BU	S & L/NLP	0.01 s to 1 h	Multiple years	Single Project → Local
urbs	72	I & ODS	BU	LP	UD (Hourly)	UD (Yearly)	Local → National
WEM*	73	S	H	S	Yearly[l]	2040	Global (25 Regions)
WeSIM	74	I & ODS	H	LP	Hour or half-hourly	1 h – multi years	National → Continental
WITCH	75	S, IDS	H	NLP, E	5 years	150 years	Global (13 regions (UD))

[a] The model includes stochastic optimisation (Stochastic Dynamic Programming (SDP)), linear programming and simulation. In the strategy evaluation, SDP is used to calculate incremental water values and heuristics is used to treat the interaction between areas. In the simulation part of the model, total system costs are minimised in a linear problem formulation.

[b] In the strategy evaluation the resolution is weekly. In the simulation it can be weekly with a load-duration curve within the week or with hourly resolution.

[c] Analytical optimisation [69].

[d] 30 min (Load flow analysis), Usually Milliseconds (Fault Level & Transient Stability).

[e] About 1-year (Load flow), Fault levels (hundreds of milliseconds), Transient (seconds).

[f] Optimisation (Mixed-Integer, Linear and Non-Linear)/Partial Equilibrium (e.g. solving Nash-Cournot with integer problems uses Mixed Integer Quadratic Programming (MIQP)).

[g] Sequential 2-year periods, 17 seasonal/diurnal blocks of non-chronological aggregate hours.

[h] U.S. (+ Canada & Mexico) – (134 Supply/demand balancing areas (+ 20 CA/+ 49 ME) & 356 renewable resource regions (+ 47 CA/+ 49 ME).

[i] 5 years until 2060, 10 until 2110, 20 until 2150.

[j] Global version: Flexible, typically 2–10 regions, National version: Norway and rest of the world.

[k] Models typically have 1–50 load zones; models have been created for California, Western U.S., Hawaii, Chile, Nicaragua, China and other regions.

[l] A new feature in WEM 2016 is the inclusion of a more detailed power market module with hourly resolution.

and is represented by a rectangle spanning the range of typical resolutions the model can possess. The transparency of the rectangles is only added to improve visual representation, and the position of the boxes have been modified to ensure readability. The figure should therefore be regarded as an illustration of the modelling landscape rather than an exact representation.

The illustration shows that the geographical scope, the temporal resolution and the approach are all related. Hybrid and top-down models populate the upper right side of Fig. 2, whereas bottom-up models are spread over the whole range. Top-down and hybrid models generally have large geographical scales and long time-steps, with the long-term development of the energy system in focus. The operation and technical details are usually omitted and replaced by macroeconomics, thus making such models top-down or hybrid.

The technological and economic features of the models are presented in Table 3. This includes features such as conventional and renewable generation, storage, grid, demand response, market modelling, emissions etc. The categories have been thoroughly explained in Section 2.2.3.

None of the models can tackle all challenges of today's energy system, but all challenges are covered by at least one of the models. There is generally a good coverage of the various technological and economic features, and modellers should be able to identify a model that can analyse most challenges related to VRES integration.

As previously mentioned, grid expansion, energy storage and demand side management are measures poised to be critical for the integration of VRES. Some earlier studies have assessed all these features, but most studies address the individual impact of one of the measures. From this review, one can identify several tools that may be used to study the effect of combining multiple measures.

Simple supply/demand modelling or spot (merit-order) of the energy/electricity market is the most common amongst the tools. However, a few of the models also have the capability to model the day-ahead market, reserve or balancing market.

Table 3
Technological and economic parameters. Abbreviations used in the table: Ren. Gen: HP – Hydropower, ROR – Run-of-river, SP – Solar Power, WP – Wind Power, ST – Solar Thermal, WaP – Wave Power, GT – Geothermal, CSP – Concentrated Solar Power, TP – Tidal Power; **Storage:** PHS - Pumped Hydro Storage, CAES – Compressed Air Energy Storage, B – Batteries, H – Hydrogen, TES – Thermal Energy Storage; **Grid:** NTC – Net Transfer Capacity; **Cost:** I – Investment, O&M – Operation & Maintenance, F – Fuel, CO2 – Carbon cost, T – Taxes, B – Balancing costs.

Models	#	Conv. Gen.	Ren. Gen.	Storage	Grid	Commodities	Demand sectors	Demand elasticity	DR	Costs	Market	Emissions
AURORAxmp	1	All	All	All (Generic)	Import/Export, NTC, DC Load Flow (SCUC/SCOPF)	Electricity, Heat	Electricity (with Heat), interface to gas models	Elastic	Yes	I, O&M, F, CO_2, B	All	Any Pollutant
BALMOREL	2	All	HP, ROR, SP, WP, ST, WaP	All	NTC	Electricity, Heat, Hydrogen & Fuels	Aggregated (Separate for Electricity and Heat)	Elastic	Yes	I, O&M, F, CO_2, T, B	Spot	CO_2, SO_2 and NO_x
Calliope	3	All	All	All	NTC	Electricity, Hydrogen, Heat & Fuels	Aggregated	Inelastic	Yes	I, O&M, F, CO_2	Supply/Demand	Any pollutant
CASPOC	4	All	All	All	Power Electronics & Circuit modelling	Electricity	Aggregated	Inelastic	No	NA	NA	No
COMPETES	5	All	HP, SP, WP, GT	PHS, CAES	NTC/DC Simplification	Electricity	Aggregated	Inelastic/Elastic (short-term)	Yes	I, O&M, F, CO_2, B, T	Spot/Balancing (Short-term)	CO_2
COMPOSE	6	All	All	All	None (Constraints can be parametrised)	Electricity, Heat & Fuels	Buildings, Transport & Industry (User-defined)	Inelastic	No[a]	I, O&M, F, CO_2, T, B	Spot, Balancing Markets	CO_2
CYME	7	All	SP, WP (All)	B	Detailed Power Simulation	Electricity	Aggregated	NA	No	NA	NA	NA
DER-CAM	8	All (Except Nuclear)	All	All	Import/Export, Power Flow	Electricity & Heat	Aggregated, Electricity, Buildings	Elastic	Yes	I, O&M, F, CO_2, T	Supply/Demand, Spot, Balancing Markets	CO_2
DESSTinEE	9	All	All	PHS	NTC	Electricity	Buildings, Transport & Industry	Inelastic	No	I, O&M, F, CO_2	Spot (Merit-order)	CO_2
DIETER*	10	All (Except Nuclear & Lignite)	WP, SP	B, H, PHS, CAES	None	Electricity	Aggregated	Inelastic	Yes	I, O&M, F, CO_2, B	Spot	No
DIgSILENT/PowerFactory	11	All	All	All (Generic)	Detailed Power Flow	Electricity	Aggregated	Inelastic	NA	NA	NA	No
EMLab-Generation	12	All	WP, SP (Generic)	All (Generic)	NTC	Electricity	Aggregated	Inelastic	No	I, O&M, F, CO_2	Spot + CO_2 market	CO_2
EMMA	13	All	WP, SP, HP, ROR	PHS	NTC	Electricity & Heat	Aggregated	Inelastic	Yes	I, O&M, F, CO_2, B	Spot	No
EMPIRE	14	All	All (Except Tidal)	All (Generic)	NTC	Electricity	Aggregated	Inelastic	Yes	I, O&M, F, CO_2	Supply/Demand	CO_2
EMPS	15	All	All	PHS	NTC (Full Load Flow possible)	Electricity	Aggregated	Elastic	Yes	I, O&M, F, CO_2, B	Spot	CO_2
EnergyPlan	16	All	All	All	Import/Export	Electricity, Heat, Hydrogen & Fuels	Buildings, Transport & Industry	Elastic	No	I, O&M, F, CO_2, T	Spot	CO_2
energyPro	17	All (Except nuclear)	All	PHS, CAES, B, TES	None	Electricity and Heat	Aggregated	Elastic	No	I, O&M, F, CO_2, B, T	Spot	CO_2, SO_2 & NO_x
Enertile	18	All	All	PHS, TES, B	NTC	Electricity & Heat	Buildings, Transport & Industry	Elastic for P2H, Inelastic otherwise	Yes	I, O&M, F, CO_2	Supply/demand	CO_2

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Table 3 (*continued*)

Models	#	Conv. Gen.	Ren. Gen.	Storage	Grid	Commodities	Demand sectors	Demand elasticity	DR	Costs	Market	Emissions
ENTIGRIS	19	All	HP, WP, SP, CSP	PHS, B, TES	NTC	Electricity	Aggregated	Inelastic	Yes	I, O&M, F, CO_2, B	Supply/Demand	CO_2
ETM (1)	20	All	All	TES	Import/Export	Electricity, Heat, Hydrogen & Fuels	Buildings, Transport & Industry	Elastic	No	I, O&M, F, CO_2, T	Supply/Demand	CO_2
ETM (2)	21	All	All (Except TP & WaP)	PHS, B, H, TES	Import/Export, NTC	Electricity, Heat, Hydrogen & Fuels	Buildings, Transport & Industry	Inelastic	Yes	I, O&M, F, CO_2, T	Supply/Demand, Spot, Balancing Markets	CO_2
ETSAP-TIAM	22	All	HP, ROR, WP, SP, ST, CSP,GT	PHS	Import/Export	Any commodity	Buildings, Transport, & Industry	Elastic	No	I, O&M, F, CO_2, T	Supply/Demand	CO_2, CH_4, NO_x, SO_x
EUCAD	23	All	All	PHS, CAES, B, H	NTC	Electricity & Hydrogen	Aggregated	Inelastic	Yes	O&M, F, B, T	Supply/Demand	None
EUPower-Dispatch	24	All	All	PHS	NTC	Electricity	Aggregated	Inelastic	Yes	O&M, F, CO_2	Supply/Demand	CO2
ficus	25	All	All	All (Generic)	Import/Export	Any commodity	Aggregated	Inelastic	No	I, O&M, F, CO_2	Supply/Demand	Any Pollutant
GCAM	26	All	HP, SP, CSP, WP, GT	PHS, H	None	Any	Buildings, Transport, Industry	Elastic	No	I, O&M, F, CO_2	Supply/Demand	CO_2 (Any)
GEM-E3	27	All	HP, WP, SP	None	Export/Import	Any Commodity	Buildings, Transport & Industry	Elastic	No	I, O&M, F, CO_2	Supply/Demand	Any Pollutant
GENESYS	28	None (Included in next version)	All	All	NTC	Electricity	Aggregated	Inelastic	No	I, O&M, F, CO_2	Supply/Demand	None (CO_2 in next version)
GridLAB-D	29	Diesel Generators	WP, SP	B	Detailed Power Flow	Electricity	Aggregated	Elastic	Yes	NA	Uniform Price Auction	NA
HOMER	30	All (Except nuclear)	All	CAES, B, H	Import/Export	Electricity & Heat	Aggregated	Inelastic	No[b]	I, O&M, F, CO_2	Supply/Demand	Any Pollutant
HYPERSIM	31	All	All	B	Detailed Power Flow	Electricity	Aggregated	NA	No	NA	NA	NA
iHOGA	32	Diesel/Petrol Generators	WP, HP, SP	H, B	Import/Export	Electricity & Hydrogen	Aggregated	Inelastic	No	I, O&M, F, CO_2	Supply/Demand	CO_2
IMAKUS	33	All	All (Exogenous)	All	Import/Export	Electricity & Hydrogen	Aggregated	Inelastic	Yes	I, O&M, F, CO_2	Supply/Demand	CO_2
INVERT/EE-Lab	34	Small-scale CHP	PV	None	None	Electricity & Heat	Buildings	Elastic	No	I, O&M, F	Supply/Demand	CO_2
IPSA 2	35	All	All	All	Detailed Power Flow	Electricity	Aggregated	Inelastic	Yes	NA	NA	NA
IRiE	36	All	HP, WP, SP	None	NTC	Electricity	Aggregated	Inelastic	No	O&M, F, CO_2, B	Reserve and Balancing market	None
LEAP	37	All	All	All	None	Electricity & Heat	Buildings, Transport & Industry	Elastic	No	I, O&M, F, CO_2	Supply/Demand	Any Pollutant
LIBEMOD	38	All	HP, ROR, WP, SP	PHS	NTC	Electricity, Heat & Fuels	Buildings, Transport & Industry	Elastic	No	I, O&M, F, CO_2, T, B	Supply/Demand, National Capacity Markets	CO_2
LIMES-EU	39	All	HP, WP, SP, CSP	All (Generic)	NTC	Electricity	Aggregated	Inelastic	No	I, O&M, F, CO_2	Supply/Demand	CO_2
LOADMATCH*	40	None	All	PHS, TES, H	None (Losses are taken into account)	Electricity, Heat & Hydrogen	Buildings, Transport & Industry	Inelastic	Yes	I, O&M, F, (+ Health and climate costs)	Supply/Demand	None
LUSYM	41	All	All	All (Generic)	Linearised DC Power Flow	Electricity	Aggregated	Inelastic	Yes	O&M, F, CO_2, B	Supply/Demand	CO_2

(*continued on next page*)

Table 3 (*continued*)

Models	#	Conv. Gen.	Ren. Gen.	Storage	Grid	Commodities	Demand sectors	Demand elasticity	DR	Costs	Market	Emissions
MARKAL	42	All	HP, WP, SP, GT	PHS, (night-day storages)	NTC	Any commodity	Buildings, Transport & Industry	Elastic	Yes	I, O&M, F, CO_2, T	Supply/Demand (Competitive, perfect foresight)	Any
MESSAGE	43	All	All	All	Import/Export	Any commodity	Buildings, Transport & Industry	Elastic	Yes	I, O&M, F, CO_2, T	Supply/Demand	Any Pollutant
NEMO	44	OCGT, CCGT, Coal (CCS)	HP, WP, PV, CST, GT	PHS, B	None	Electricity	Aggregated	Inelastic	Yes	I, O&M, F, CO_2	Spot	CO_2
NEMS	45	All	All (except TP & WaP)	PHS, B, TES	Import/Export	Electricity & Heat (Partly Hydrogen in transport)	Buildings, Transport & Industry	Elastic	No	I, O&M, F, CO_2, T	Supply/Demand	CO_2, SO_2 and NO_x
Oemof (SOLPH)	46	All	All	All	Import/Export, NTC	Electricity, Heat, Hydrogen & Fuels	Buildings, Transport & Industry	Inelastic	Yes	I, O&M, F, CO_2, T, B	Supply/Demand	Any pollutant
OpenDSS	47	All (Generic)	SP (Others Generic)	All (Generic)	Full Multiphase AC Load Flow; Dynamics	Electricity	Aggregated (optionally disaggregated)	Inelastic	Yes	NA	NA	NA
OSeMOSYS	48	All	All	All	None	Electricity	Aggregated	Inelastic	Yes	I, O&M, F, CO_2, B	Supply/Demand	Any Pollutant
PLEXOS	49	All	All	All (Generic)	[c]	Electricity (with Heat), Gas and Water	Buildings, Transport & Industry	Elastic	Yes	I, O&M, F, CO_2, B	[d]	All (Generic)
POLES	50	All (25 explicit technologies)	All (16 explicit technologies)	PHS	None (Import/Export)	Electricity, Fuels	Buildings, Transport & Industry	Elastic	No	I, O&M, F, CO_2, T	Supply/Demand (Carbon price)	GHG
PowerGAMA	51	All (Generic)	All (Generic)	All (Generic)	Linearised DC Power Flow	Electricity	Aggregated	Inelastic	No[e]	Marginal Costs	Supply/Demand (Perfect)	None
PRIMES*	52	All	All	All	DC linearised Optimal Power Flow	Electricity, Heat & Hydrogen	Buildings, Transport & Industry	Elastic	Yes	I, O&M, F, CO_2, T	Supply/Demand	CO_2
ProdRisk	53	Thermal Power Plants	HP, WP	PHES	None (Exists a prototype with detailed grid)	Electricity	Aggregated	Yes	No	No fixed price	Spot (Capacity Market under development)	None
PyPSA	54	All	All	All (Generic)	Non-linear/Linear Power Flow, NTC	Any commodity	Aggregated	Inelastic	Yes	Capital Cost & Marginal Cost	Supply/Demand	CO2
RAPSim	55	None (Under development)	WP, SP	None (Under development)	Detailed Power Flow	Electricity	Building	Inelastic	No	None	None	None
ReEDS	56	All	All (Except Tidal)	All (Except Hydrogen)	Linearised DC Power Flow	Electricity	Aggregated	Inelastic	Yes	I, O&M, F, CO_2, T	[f]	CO_2, SO_2, NO_x + Mercury
ReMIND	57	All (Coal, Oil, Gas, Uranium, Biomass)	HP, SP, WP, GT	All (Generic)	None	Electricity, Heat, Hydrogen & Fuels	Buildings, Transport & Industry	Elastic	Yes	I, O&M, F, CO_2	Supply/Demand (Pareto/Nash)	Any Pollutant
REMix	58	All	All	All	NTC, DC simplification	Electricity, Heat & Hydrogen	Aggregated	Inelastic	Yes	I, O&M, F, CO_2	Supply/Demand	CO_2
renpass	59	All	HP, WP, SP, GE, ROR	PHS, CAES, B	NTC	Electricity	Aggregated	Inelastic	No	I, O&M, F, CO_2	Spot	CO_2
RETScreen	60	All	All	B	Central/Isolated/Off-Grid (Import/Export)	Electricity & Heat	Buildings & Industry	Inelastic	No	I, O&M, F, CO_2, T	Supply/Demand	GHG
SAM	61	Conventional Thermal & Biomass	SP, ST, CSP, WP, GT	B, TES	None	Electricity	Aggregated	Inelastic	No	I, O&M, F, T	None (E.G. Power Purchase Agreement))	None

(*continued on next page*)

Table 3 (*continued*)

Models	#	Conv. Gen.	Ren. Gen.	Storage	Grid	Commodities	Demand sectors	Demand elasticity	DR	Costs	Market	Emissions
SIMPOW	62	All	All	None	Detailed Power Flow	Electricity	Aggregated	Inelastic	NA	NA	NA	NA
SIREN	63	All	All	All (Generic)	NTC	Electricity	Aggregated	Inelastic	No	I, O&M, F	Supply/Demand	CO_2
SNOW	64	All	All	None	Import/Export	Any commodity	46 industries, households & public sector	Elastic	No	I, O&M, F, CO_2, T	Supply/Demand	Any Pollutant
stELMOD	65	All	HP, WP, ROR & SP	PHS	NTC, DC simplification	Electricity, Heat	Aggregated	Inelastic	No	O&M, F, CO_2, B	Spot, Intra-day, Reserve-Market	CO_2
SWITCH	66	All	All (Generic)	All	[g]	Electricity (Partly transport)	Aggregated	Elastic/ Inelastic	Yes	I, O&M, F	Supply/Demand	CO_2
Temoa	67	All	All	All	NTC	Any commodity	Buildings, Transport & Industry	Inelastic	No	I, O&M, F	Supply/Demand	Any Pollutant
TIMES	68	All	All	All	NTC	Any commodity	Buildings, Transport & Industry	Elastic	Yes	I, O&M, F, CO_2, T, B	[h]	Any
TIMES-Norway	69	All (Except Coal)	All (Except GT (for el), CSP, WaP & T)	B, TES	NTC	Any commodity	Buildings, Transport & Industry	Inelastic	No[i]	I, O&M, F, CO_2, T	[h]	CO_2
TIMES-Oslo	70	All (Except Coal & Nuclear)	All (Except GT (for el), CSP, WaP & T)	None	NTC	Any commodity	Buildings, Transport & Industry	Inelastic	No	I, O&M, F, CO_2, T	[h]	CO_2
TRNSYS17	71	All (Except Nuclear)	SP, WP, ST, CSP, GT	B, H, TES	[j]	Electricity, Heat, Hydrogen & Fuels	Building and Industry	Inelastic	NA	NA	NA	NA
urbs	72	All	All	All (Generic)	NTC (+ Linearised Load Flow)	Any Commodity	Aggregated	Inelastic	Yes	I, O&M, F, CO_2, B	None	Any Pollutant
WEM*	73	All	All	All	None	Electricity, Heat, Hydrogen & Fuels	Building, Transport & Industry	Elastic	Yes	I, O&M, F, CO_2, B	Supply/Demand (+ Spot)	CO_2
WeSIM	74	All	All	All	NTC	Electricity, Heat & Gas	Aggregated	Inelastic	Yes	I, O&M, F, CO_2, B	Supply/Demand	CO_2
WITCH	75	All	HP, WP, SP, CSP	TES, B	NTC	Any commodity	Aggregated	Elastic	Yes	I, O&M, F, CO_2, B	Supply/Demand + CO_2-Market	Any Pollutant

[a] Can be parametrised.
[b] Can model controllable loads in a variety of ways.
[c] Import/Export, NTC, DC Load Flow, AC Load Flow (linearised approximation using Fixed or Variable Shift Factors - PTDFs), SCOPF and FBMC.
[d] Physical & Financial Forward Power Markets (Year-Ahead, Month Ahead, Spot, Intra-day) Balancing Market, All Reserve-Markets, Capacity Market, Gas Market, Water Market, Perfect Competition, Nash-Cournot market modelling or Bertrand pricing.
[e] A simplified model for flexible demand is included.
[f] Energy market (supply/demand balance), Capacity market (planning reserve margin requirement), Ancillary Service market (operating reserves), Renewable Energy Credit (REC) market (state Renewable Portfolio Standards).
[g] SWITCH uses a simplified transport model for investment planning, but can also use security-constrained AC power flow for production cost modelling.
[h] Supply-Demand (Competitive with perfect foresight or n-period myopic).
[i] Will be implemented In next version.
[j] Usually treats the grid as an infinite power source/sink, but has models for transmission losses and grid outages.

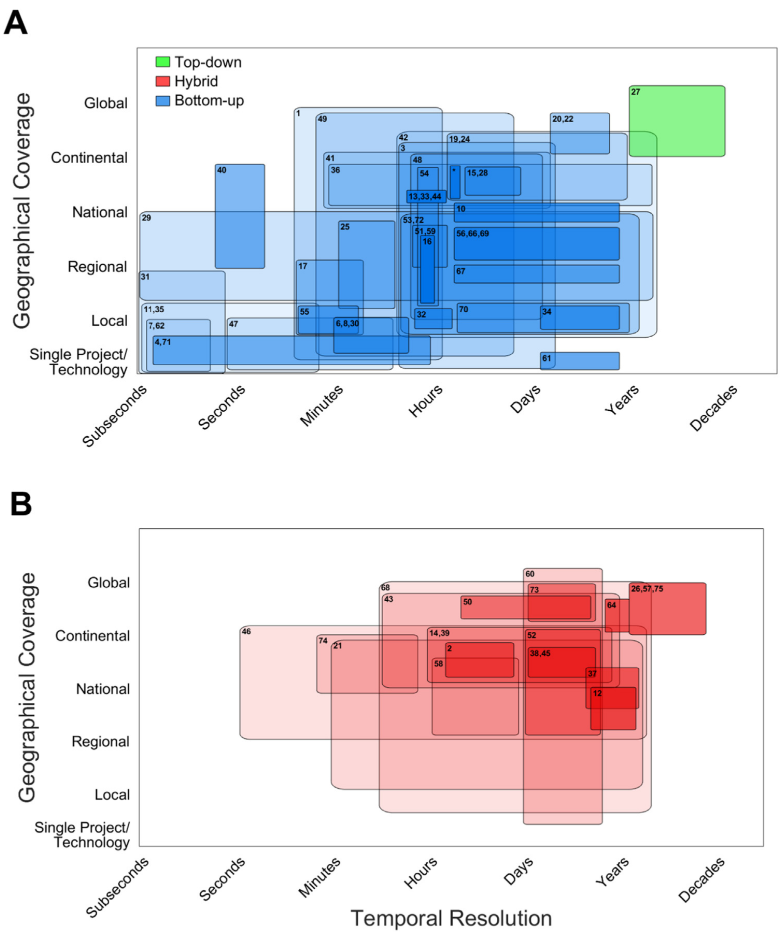

Fig. 2. Illustration of geographical coverage vs temporal resolution in the assessed models. The modelling approach is indicated by the colour of the rectangles, with transparency added for visual representation only. Panel A shows pure bottom-up and top-down models, and panel B shows hybrid models. For full interpretation of the figure, the reader is referred to the web version of this article. The rectangle marked with an asterisk (*), corresponds to models number 5, 9, 18, 23, 63 and 65.

4. Discussion and conclusions

This review has shown that there are numerous energy modelling tools currently available, capable of serving most needs from modelling of small-scale power systems to the global energy system. Grid expansion, energy storage and demand side management were earlier mentioned as key technologies and measures for a successful integration of VRES in the grid. Among the reviewed models, these measures are well represented. There are, however, some challenges faced by current modelling tools as well as future modelling needs.

4.1. Representation of variability

Many studies have looked into the effect and possibility of integrating wind and solar into the existing, fossil fuel dominated energy system. They all represent the geophysical data in distinct ways: Timescales ranging from seconds to several years, spatial resolutions ranging from a few kilometres to several latitudes, as well as the use of statistical representations [221–225]. The coarsest representation of variability is found in computable general equilibrium or partial equilibrium models, often with yearly aggregated data.

In long-term energy models, which are usually used to define the composition of and pathways to a future energy system, the temporal variability is often underrepresented [226]. A too coarse time-step can give poor estimation of the operation of the system, leading to unfavourable investments, overestimation of the share of VRES and an underestimation of the costs.

Welsch et al. used OSeMOSYS and a combined TIMES-PLEXOS model to study the Irish electricity system [142]. The medium to long-term energy model OSeMOSYS was first set up using 12 time periods each year, and was compared to a soft-linked combination of TIMES-PLEXOS using 8784 time periods over one year. Analysis of 2020 showed that the OSeMOSYS model allocated 21.4% of the dispatch to wrong generation capacities, by for example overestimating the use of wind energy. However, Welsch et al. further shows that by adding operational constraints in an enhanced OSeMOSYS model, without increasing the temporal resolution, the results from the TIMES-PLEXOS model were reproducible. They also extended the analysis to 2050, showing that the simple OSeMOSYS model, whose results are representative of conventional long-term energy models, invested in

14.1% less capacity and led to 14.5% lower investments than the enhanced model. They did not, however, extend the use of TIMES-PLEXOS to 2050, as computational costs become too high over such a long time-horizon with a high resolution and operational detail.

Similarly, Poncelet et al. used TIMES to evaluate the impact of utilising long-term energy models with a low temporal resolution [227]. Their version of the TIMES model was calibrated to Belgium and used 12 representative time-slices per year. It was compared to a unit-commitment (UC) model (mixed-integer linear formulation based on Van den Bergh et al. [228], later named LUSYM [124]) with an hourly resolution. They showed that the TIMES model invested in less VRES capacity than the UC model towards 2050, but their electricity generation shares were equal; showing once again that a low temporal resolution leads to an overestimation of VRES penetration and thus and underestimation of the necessary investment.

LEAP, MARKAL/TIMES and EnergyPLAN were used by Haydt et al. [229] to study the island of Flores (Azores) in the Atlantic Ocean through three different balancing methods (integral with load-curve of 9 time slices, semi-dynamic with 288 time periods and a dynamic approach with hourly modelling). Haydt et al. found that the models which did not consider the variability well enough overestimated the generation of VRES, therefore underestimating the necessary installed capacity as well as CO_2 emissions.

Tackling both the operational and planning issues of energy systems can, as has been shown above, be done by either linking models with different features or by adding capabilities within a model itself. As an example of the latter, Seljom et al. [230] developed a stochastic TIMES model, that dealt with the short-term uncertainty experienced in electricity generation and heat demand in buildings. Similarly, the EMPIRE model is a stochastic optimisation model, which simultaneously deals with the long-term evolution of the European electricity system as well as its operation [59]. Després [81] combined two models, EUCAD and POLES, respectively a power system optimisation model and a long-term energy model. EUCAD optimises the operation of the European power system every 24 h, taking into account the power system balance, international exchanges and system constraints such as operating points, on- and off-time, ramping and frequency reserves. This detailed representation of the power system was then combined with POLES, which covers the long-term evolution of demand, costs, and technological evolution and makes investment decisions for generation, storage and grid capacities. In addition, Jaehnert et al. has coupled the day-ahead market model EMPS with IRIE, a model that concerns reserve procurement and system balancing [231].

It is evident that considerations regarding VRES variability and operation are key aspects in present modelling, and represent challenges that become more and more important the larger the share of VRES in the energy mix becomes.

4.2. Consumer participation, electrification and sector coupling

Through distributed generation and demand side management, consumers are to an increasing extent becoming involved in the electricity system. More and more consumers are becoming prosumers, delivering power to the grid through distributed generation units as well as drawing power from the grid when local production is not sufficient. This affects both the distribution grids and the whole energy system on a larger scale. Consumers will also have to participate in demand response, which involves an intelligent management of their flexible loads. It will thus be important to capture consumer responses to changes in electricity and policies in energy modelling tools. Rai and Henry [232] modelled consumer energy choices using an agent-based simulation model. They show that such models can increase our understanding of consumer choices, knowledge that will be increasingly important as consumers become more involved in the energy system.

Decarbonisation of the electricity sector is a challenge that can, in theory, relatively easily be solved by replacing conventional fossil fuelled power generators with already mature and increasingly cost-competitive renewable technologies. The transport, heating and industrial sectors, however, are not that straight forward. One possible solution is to use different types of fuels, such as hydrogen or biofuels. Another possible solution is electrification, through for example switching to electric vehicles, electric water heaters, heat pumps, electric induction stoves, electrifying industrial equipment and so on. Switching from fossil fuelled vehicles to electric vehicles will not only enable decarbonisation of transport, but also lead to a lower primary energy demand as electric vehicles are much more efficient than their fossil fuelled counterparts [233]. This is also the case for other appliances, such as electric heat pumps for space and water heating with efficiencies of 200–300% [234]. The extent of future electrification is uncertain, but it can be hypothesized to lead to a significant increase in the electricity demand.

A more interconnected energy system, where the power, heat, industrial and transport sectors are closely linked, can help accommodate generation from variable renewables as well as abate emissions. Connolly et al. [235] recommends avoiding the traditional one-sided focus on how the power-sector alone can integrate VRES, and rather look into the synergies that can be achieved by merging the power, heating and transport sectors through a “Smart Energy Systems approach”. They argue that measures such as battery electric vehicles, thermal storage, heat pumps and various types of fuel storage could provide increased flexibility for VRES, and thus enable higher penetration rates and even 100% renewable energy systems. A first step towards a 100% renewable-based Irish energy system was investigated by the use of EnergyPLAN [236], a modelling tool that can take into account the coupling between the electricity, heat and transport sectors [64]. Similarly, in a study combining the LOADMATCH grid integration model and the GATOR-GCMOM global climate/weather model, Jacobson et al. [225] assessed the energy system of the contiguous United States in 2050–2055 consisting of 100% renewable energy for all sectors (electricity, transportation, heating/cooling, and industry). They showed that the system is delivered at a low cost and is reliable with no load loss for the six simulated years. One of the main factors for the success of this system was the interplay between the various sectors, with hydrogen and heat as major contributors. Due to the importance of sector coupling in integrating large amounts of VRES, it is suggested that this is given more attention in future modelling studies.

4.3. Impacts and links beyond the energy system

Agenda 2030 [237], including its 17 Sustainable Development Goals and 169 targets, constitutes a global framework for sustainable development. In order to find a sustainable path forward, there is a need to address the interaction between different goals and solutions for energy supply, food production, protection of climate, the environment and ecosystem functions and many other aspects relevant to the livelihoods of people. This requires knowledge about the potential impacts and the links between them. Possible impacts of different energy systems are numerous and diverse including climate impacts due to CO_2 emissions, impacts on human health and the environment due to emissions of pollutants, impacts on changing land use e.g. for production of biofuels, local environmental impacts of hydropower dams, and impacts on availability of water and scarce resources [238,239].

Several studies have assessed external impacts of present and future energy systems through linking electricity or energy systems models with other types of models. Berrill et al. [240], Rauner and Budzinski [241], and Garcia-Gusano et al. [242] all couple some form of life cycle analysis modelling tool to their energy system models. E.g. Berrill et al. [240] coupled the energy model REMix with the integrated life cycle analysis modelling framework THEMIS to study different electricity scenarios for Europe towards 2050 and their impacts on climate change, freshwater ecotoxicity, particulate matter formation, mineral resource depletion and land occupation. They find that impacts of wind and solar energy do not significantly compromise the climate benefits of utilising these energy resources, but that VRES-based systems require more infrastructure leading to much larger mineral resource depletion impacts than fossil fuel systems, and greater land occupation impacts than systems based on natural gas.

Buonocore et al. [243] developed a linked electric dispatch and public health impact assessment model (EPSTEIN), in order to assess the public health benefits of displacing emissions from fossil-fuelled power plants through energy efficiency and renewable energy. Furthermore, Abel et al. [244] investigated future health impacts of power sector-related air pollution in the eastern United States, resulting from increased air conditioning usage in a warming climate. By using a comprehensive modelling system consisting of five linked models to assess the meteorology (WRF), building electricity demand (RBESS), power sector (MyPower), air quality (CMAQ), and health impacts (BenMAP), they estimated that increased air conditioning potentially can cause up to a thousand $PM_{2.5}$- and O_3-related deaths. Also looking at the United States, Wiser et al. [245] used ReEDS to estimate the benefits of increased penetration of solar energy in the United States on greenhouse gas emissions, air pollutants and water usage.

While it may not be desirable or even possible to attempt to quantify all impacts of an energy system in modelling exercises, in view of Agenda 2030 [237] it seems reasonable to expect that energy system modellers in the future need to be aware of and in some cases include external impacts in their modelling tools.

4.4. Validation and transparency

One of the strengths of power system analysis tools is that, unlike long-term energy models, their results are in fact directly testable and verifiable. E.g. IPSA 2 has been developed for over 30 years and has gone through extensive testing and validation against real life results to ensure accurate modelling results [246]. Lammert et al. [53] implemented a generic PV system model in DIgSILENT PowerFactory, achieving perfectly matching results in comparison with a Renewable Energy Model Validation tool that had been validated against real measurements. On a larger scale, the model HYPERSIM was tested and validated on the large AC/DC transmission network of Hydro-Québec [101], SIMPOW performed validation through the Gotland HVDC project [180] and PowerGAMA validated its power flow results of most of the European transmission network by comparison to actual data from ENTSO-E [151].

On the other hand, neither long-term energy tools nor general computable equilibrium models can be properly validated [13,247]. Their long time horizons make it practically impossible to compare their outcomes with real-world observations, and changes happening through time and external events not taken into account in the model can alter the structure of the system [248]. For example, it can not be excluded that political events or unforeseen major technological breakthroughs greatly change how the future energy system will look like. Nonetheless, such models give valuable insight on a multitude of aspects; such as the composition of the future energy systems and possible pathways of how to get there, the effect of various policies, changes in market dynamics etc.

Modelling tools may be highly sensitive and dependent on their assumptions and data used. In many current models, source-code, assumptions and data are not accessible, making it impossible for independent actors to reproduce the work. Transparency and openness in energy modelling should be encouraged, especially since many modelling tools play important roles in policy-making processes. NEMS and PRIMES have for example been used for policy making respectively in the U.S. and for the European Commission [134,249]. As underlined by Pfenninger et al. [250], increased openness leads to improved quality of research, more effective links between science and policy, increased productivity and also increased relevance to important societal debates.

4.5. Future modelling needs

Forecasting of VRES, in particular of wind, is a challenging task. The motion in the atmosphere is chaotic and hard to predict accurately. Only a small change in the initial conditions in a weather model can change its predicted outcome completely. The electricity market is highly dependent on accurate forecasts of wind and solar energy production, both in day-ahead markets, for balancing and reserves planning as well as for longer-term forecasts (i.e. months and seasons). Pineda et al. [251] showed for example that not taking into account forecast errors in expansion planning models can lead to highly suboptimal planning in terms of cost efficiency or penetration of renewables.

The present review has shown that only a few current modelling tools take into account the uncertainty of VRES generation. Most tools are deterministic and VRES generation is based on historical meteorological data. Some examples of models taking into account uncertainty are; EMPS, which considers uncertainty in hydro inflow and market conditions [156]; E2M2, which considers uncertainty in VRES power production by using a multi-stage stochastic program including a recombining tree formulation [252]; and in [230] stochasticity and uncertainty were included for PV production, wind production, hydro production, heat demand in buildings and electricity prices.

Climate change can be responsible for altering energy demand or the resource potential of renewable energies in the long-term [253,254]. Barstad et al. [255] looked at the present and future offshore wind power potential in northern Europe based on downscaled (high resolution) global climate runs. They found that a power reduction of 2–6% is expected in most areas. Similarly, Jerez et al. [256] investigated future solar power outputs in Europe using the EURO-CORDEX ensemble of high resolution climate projections together with a PV production model. They showed that future European PV production would lie in the range of − 14 to + 2% compared to today. However, the largest decrease is seen in Northern Europe where much PV development is not expected, and in Southern Europe the results even show a slight positive trend. Similarly, increased temperatures from global warming can lead to changes in the electricity demand [257,258]. This raises the question whether effects of climate change on regional resource potential should be taken into account in long-term energy modelling tools.

With increased development of offshore wind farms in particular, interaction between the farms themselves is an increasing concern. Similarly to the wake effect within a farm, the farm itself can lie in the "shadow" of another farm and thus generate less electricity. Studies performed at the FINO-1 research platform showed that the effect from the closely placed Alpha Ventus wind farm was responsible for a turbulence intensity increase and a wind speed reduction of up to 50% [259]. With increased offshore development this effect should be accounted for when modelling.

4.6. Conclusion

This paper reviews 75 state of the art energy and electricity modelling tools, ranging from small-scale power system analysis tools to global long-term energy models. The reviewed models offer a broad range of capabilities, aiding modellers in identifying suitable models for their own purposes. The models are categorized by their general logic, spatiotemporal resolution and technological and economic parameters, with validated information as of the date of submission for 95% of the models.

Although this paper shows the massive capabilities of the current landscape of modelling tools, there are still some challenges related to representation of spatiotemporal variability and openness as well as the demand side that should be addressed in future model development and application.

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Supplementary material

An Excel file containing all the information about the reviewed models can be found in the online version of this paper.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.rser.2018.08.002.

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Paper II

6.2 Transitioning remote Arctic settlements to renewable energy systems - a modelling study of Longyearbyen, Svalbard

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Transitioning remote Arctic settlements to renewable energy systems – A modelling study of Longyearbyen, Svalbard

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HIGHLIGHTS

- We present a new stochastic long-term energy model for a remote Arctic settlement.
- We show the importance of a proper representation of solar and wind variability.
- An energy system based on renewables is found feasible, reliable and affordable.
- Energy efficiency plays an important role in a transition to a low carbon settlement.
- Allowing some CO_2 emissions reduces costs and improves energy security.

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ABSTRACT

As transitioning away from fossil fuels to renewable energy sources comes on the agenda for a range of energy systems, energy modelling tools can provide useful insights. If large parts of the energy system turns out to be based on variable renewables, an accurate representation of their short-term variability in such models is crucial. In this paper, we have developed a stochastic long-term energy model and applied it to an isolated Arctic settlement as a challenging and realistic test case. Our findings suggest that the stochastic modelling approach is critical in particular for studies of remote Arctic energy systems. Furthermore, the results from a case study of the Norwegian settlement of Longyearbyen, suggest that transitioning to a system based on renewable energy sources is feasible. We recommend that a solution based mainly on renewable power generation, but also including energy storage, import of hydrogen and adequate back-up capacity is taken into consideration when planning the future of remote Arctic settlements.

1. Introduction

Remote Arctic energy systems are usually characterised by a dependence on imported fossil fuels [1,2]. Concerns about volatile fuel costs, energy security, and climate change give rise to many remote Arctic communities looking towards renewable energy sources as potential solutions. Rapid cost-reductions and technological development have led to renewables becoming an increasingly attractive option. Particularly solar and wind are emerging as mature and cost-competitive technologies, even for energy systems in remote Arctic locations.

The transition to future energy systems is often aided by the use of energy modelling tools. Several tools exist, with various capabilities, features and applications ranging from analysis of detailed power systems to the global energy system (see reviews by Connolly et al. [3], Ringkjøb et al. [4], Hall & Buckley [5] and Foley et al. [6]). Many previous modelling studies have looked at remote isolated communities, but there are only a few focusing on Arctic locations [7,8]. For example, the HOMER (Hybrid Optimization of Multiple Energy Resources) modelling tool [9] was applied to study the electricity system serving the small settlement at the island of Grimsey located north of Iceland (66.5°N) [1]. They analysed three scenarios for delivering electricity, respectively a diesel-wind, diesel-wind-hydrogen and a wind-hydrogen scenario. Their results showed that a system consisting of wind, hydrogen and diesel was recommended, achieving a renewable energy fraction of 92% and a payback period of less than four years. Furthermore, the TIMES (The Integrated MARKAL-EFOM System) modelling framework [10] was used to study the energy system at the Faroe Islands (62°N) [11], highlighting the importance of electrification of heating and concluding that renewable energy technologies will be competitive with fossil fuels in a very short time, even in the Arctic. Streymoy, the largest island on the

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Faroe Islands, was also one of six islands investigated in a study using a MATLAB/Simulink model to determine cost-optimal system configurations [12].

A larger literature has addressed remote and isolated locations at lower latitudes, such as the island of Pulau Ubin north-east of Singapore [13], the island of Dia in the Cretan Sea [14] and other locations in the Mediterranean [15] Even though the climatic conditions in such locations are vastly different from the Arctic, several similarities make these studies relevant also in an Arctic context. Many of these locations are also dependent on imported fossil fuels, have a need of improving energy security and a large distance to highly populated areas. They are therefore evaluating renewables as alternatives [8].

Wind and pumped hydro storage (PHS) was for example evaluated for increasing the share of renewables and aid in desalination of water on the S.Vicente Island in Cape Verde in a study using the modelling tool H_2RES [16]. Furthermore, a 100% renewable electricity supply for Reunion Island was modelled in TIMES [17], with large amounts of solar, biomass, and important contributions from storage and demand response. TRNSYS [18] was used in combination with HYDROGEMS [19] in a modelling study of the former wind/hydrogen demonstration project at Utsira in Norway [20]. The goal of this demonstration project was to demonstrate how hybrid renewable energy and hydrogen systems could provide electricity to communities in remote areas. The authors concluded that the project successfully demonstrated the potential of wind/hydrogen systems to supply remote locations, but that technical improvements and cost reductions were needed to be competitive with existing solutions.

In this study, we use the TIMES modelling framework to develop and apply a new stochastic model for isolated Arctic settlements. The model takes into account the variability of short-term solar and wind generation as well as the uncertainty in electricity and heat loads. A common approach, also when modelling larger energy systems, is to treat solar and wind generation as deterministic inputs. This has previously been shown to potentially overestimate the contribution from variable renewable energy sources and lead to suboptimal investments [21–23]. Long term persistence is characteristic for geophysical time series including solar and wind resources [24]. In a harsh Arctic climate, where security of energy supply is crucial for the inhabitants, taking into account the possibility of periods with low solar and wind resources is highly important.

Stochastic modelling of short-term variability in TIMES is a relatively new technique, first applied in a study of the Danish energy sector [22], but which to the authors' knowledge has never been applied to local isolated energy systems. Our hypothesis is that a stochastic approach is even more important in a small isolated energy system than in a large national or international system. As has been pointed out by Connolly et al. [3], TIMES models have mainly been applied to study energy systems on larger scales up to the global energy system, and are not commonly used to assess remote and isolated communities. However, we believe that the stochastic approach enables the use of TIMES-based long-term energy models to study small isolated energy systems, thus widening the range of possible applications of the TIMES modelling tool.

The importance of a stochastic approach is investigated through a case study focusing on the Norwegian high-Arctic settlement of Longyearbyen (78.2°N). Presently, the settlement covers its needs for electricity and heat from Norway's only coal-fired power plant supplied by locally mined coal. With a declining coal industry, an old energy infrastructure, and the use of greenhouse-gas-emitting coal as the main source of energy, there is a need of planning for securing the future energy supply. This makes this study highly relevant to decision-making, and well suited for investigating the importance of a stochastic modelling approach for remote communities in general.

The objective of the present study is to develop a dynamic model to analyse and optimise an affordable and reliable future supply of electricity and heat primarily based on renewable energy sources and test it on a realistic case where necessary data are available. The model selects which energy system components to invest in over time based on bottom-up cost estimates for available components, minimizing total discounted investment and operational costs over the time period. The study demonstrates the importance of a realistic representation of solar and wind variability in long-term energy models, through the application of a stochastic modelling approach.

2. The Longyearbyen case-study

Longyearbyen was founded in 1905 for coal mining purposes, and is located on the Svalbard archipelago barely a thousand kilometres from the North Pole (see Fig. 1). Now, the more than century long coal mining era is coming to an end. Years of low coal prices have led to economic difficulties for the state-owned mining company "Store Norske Spitsbergen Kulkompani». In autumn 2017, the Norwegian government decided a permanent closure of the mines Svea and Lunckefjell [25]. This leaves the smaller mine number 7 as the only Norwegian coalmine to be kept in operation on Svalbard, and its main purpose is to supply the power plant in Longyearbyen. The coal reserves in mine 7 are expected to be able to supply the power plant for 10 more years, after which coal has to be imported if a new energy system is not in place.

Since Longyearbyen houses the only coal-fired power plant in Norway, there is particular political focus on reducing emissions from Longyearbyen. The power plant is the main component of the current energy system in the settlement, providing about 40 GWh electricity and 70 GWh heat to the about 2100 year-round residents and 150 000 person-days of visitors, mostly in summer [26,27]. Most of the electricity is consumed in the industrial sector, whereas households and the service sector consume the majority of heat [28]. The power plant was built in 1982 and faces challenges regarding ageing equipment, though recent and comprehensive upgrades have extended the potential lifetime of the plant for about another 20 years [27].

In addition to the coal-fired power plant, there are five diesel generators to cover peak electricity demand and to serve as reserve generation capacity. There is also a reserve heat-exchanger that can be fed directly with steam from the two coal-fired boilers in case of failure on the back-pressure turbine. Six oil-fired boilers are also placed around in the district heat network for reserve and to cover peak heat demand. There is also a small amount of solar PV installed in the settlement, about 57 kW on the airport and about 28 kW on residential buildings in Longyearbyen [29]. In total, the energy supply in Longyearbyen emits about 60 000 tons CO_2 annually [11].

Against this background, there is a need of planning the future energy supply of Longyearbyen. The Norwegian Ministry of Petroleum and Energy has already started investigating different options, and will decide the future of Longyearbyen's energy system in the near future [30]. The Norwegian Government stresses that the future energy supply in Longyearbyen should be sustainable and cost-effective, as well as provide adequate security of supply.

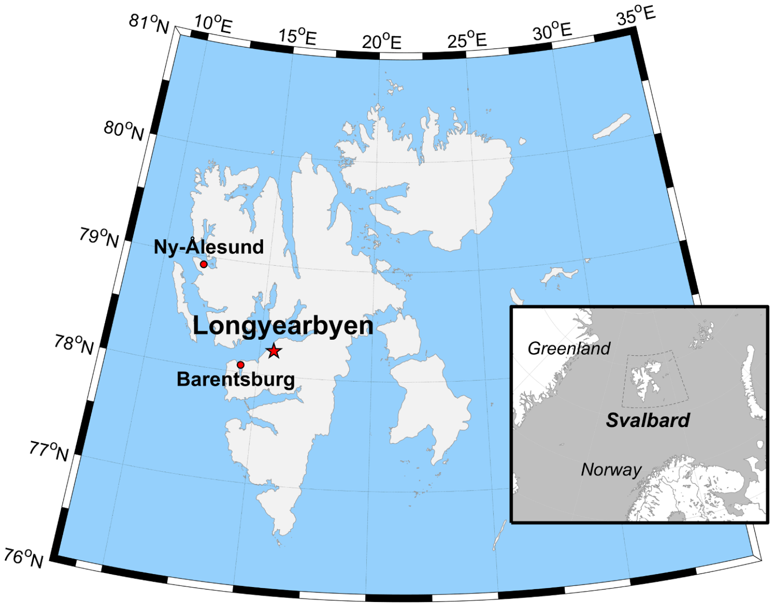

Fig. 1. Map of Svalbard and its surroundings.

3. Modelling methodology

3.1. TIMES-Longyearbyen

TIMES (The Integrated MARKAL-EFOM System) is a modelling framework widely used to develop models of local, national, international or global energy systems [10]. It follows a bottom-up approach, and performs long-term analyses of the entire or parts of the energy system. The TIMES modelling framework uses linear programming to minimise the total system cost, through optimal decision making on infrastructure investments, systems operation and imports of energy carriers. An extensive documentation detailing the TIMES modelling framework can be found in [10].

Based on the TIMES modelling framework, we have developed and applied the stochastic long-term energy model TIMES-Longyearbyen in this study. TIMES-Longyearbyen consists of the single isolated region of Longyearbyen. The base-year is 2015, and the base case global discount rate has been set to 4% in compliance with recommendations from the Norwegian Ministry of Finance in long-term socioeconomic studies [31]. We also assess the sensitivity of the model results on the discount rate in Section 4.6. The currency chosen is Norwegian kroner (NOK), and all costs, prices etc. are given in 2015-NOK.

The model horizon is from 2015 to 2050, and investments are made every 5th year (Fig. 2). In order to represent the operation of the system, e.g. through demand profiles and variable renewables, we use a high temporal resolution within each period (Fig. 2). Each year is represented by 192 time-slices, distributed over 24 h over two days (one weekday and one weekend day) per season; spring (March, April and May), summer (June, July and August), autumn (September, October, and November) and winter (December, January and February).

Load profiles for electricity and heat have been derived from two real datasets of heat and energy generation from the power plant in Longyearbyen (Longyear Energiverk), given on an hourly basis for 2017 and 2018 [32]. The datasets were used to calculate representative daily load profiles, and as input for the stochastic modelling.

For each of these representative time-slices, the demand of heat and electricity must be covered by the set of technologies in the model. For the present study, in addition to the current system in Longyearbyen,

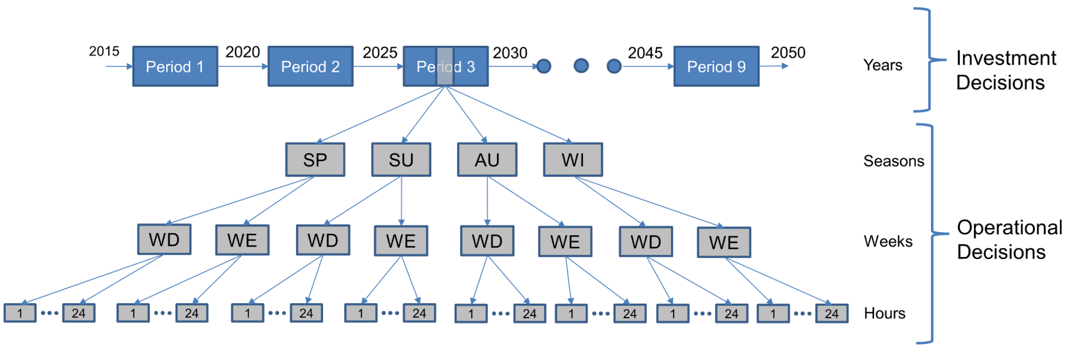

Fig. 2. Time-slice division in TIMES-Longyearbyen.

we have included a broad set of technologies available for future investments (solar photovoltaics, solar thermal, onshore- and offshore wind, hydrogen electrolysers, hydrogen storage, hydrogen fuel-cells, lithium-ion batteries, geothermal and seawater-based heat pumps, electric boilers, underground thermal energy storage, diesel generators, gas turbines, gas cogeneration plants and energy efficiency measures). Costs of these technologies are as far as possible based on recent data from the Norwegian Water Resources and Energy Directorate with the aim to use costs that are both relevant in a Norwegian context and state of the art in a quickly changing energy sector [33,34]. The present and future costs of these technologies, as well as their technological parameters (efficiency, technical lifetime etc.), are summarised and referenced in Table S1 in the supplementary materials.

Several technologies were omitted from the study due to qualitative considerations, e.g. hydropower and biomass due to lack of potential. Another example is electricity generation through an Organic Rankine Cycle (ORC) using a low temperature geothermal heat source. Preliminary test drillings have shown promising conditions for geothermal energy in and around the settlement, with ground temperatures significantly higher than experienced in mainland Norway [35]. With its independence of weather conditions, year-round availability and its ability of serving as a base-load generator, geothermal electricity may become a useful component of the energy system in Longyearbyen. However, due to the high uncertainty, both in terms of the actual resource potential and in terms of costs, geothermal electricity was not assessed in this study.

Solar PV panels with single-axis tracking has a slightly higher performance than fixed panels, but are omitted from the study due to higher costs and the reduced durability associated with moving parts in harsh arctic conditions with both snow and ice.

Another potential technology not modelled in this study, is carbon capture and storage (CCS). Studies concerning the potential of CCS for Longyearbyen have been undertaken at the University Centre in Svalbard (UNIS) [36]. CCS could be an option to extend the operation of the coal-fired power plant or used with new gas based generators. We have not included CCS due to uncertainties about storage integrity, costs and maturity of related technologies.

3.2. Projection of end-use energy demand

Projections of future end-use energy demand are supplied exogenously to TIMES-Longyearbyen, and are important drivers for modelling results. Since Longyearbyen is highly influenced by policy, this is a challenging task.

Fig. 3 shows the historic evolution of heat- and electricity demand in Longyearbyen from 2000 until 2015. A sharp population increase from about 1500 to about 2100 residents between 2000 and 2010 was a strong driver for increased heating needs in the settlement [37]. In the period between 2010 and 2015, the population was quite stable and lead to the heat demand stabilizing around 70 GWh (see Fig. 3). On the other hand, the generation of electricity has been relatively constant

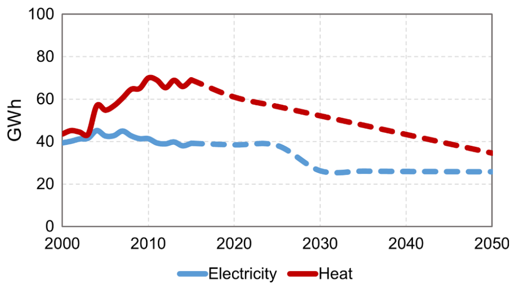

Fig. 3. End use demand projection.

through the whole period, which can be explained by a gradual shift from electricity demanding mining activities to less demanding activities such as tourism, culture and education. In our calculations of future end use energy demand, we have assumed that the population is kept stable at the current level.

The energy demand is split into three main sectors; households, services and industry, where all three sectors require electricity and heat as an energy service. We follow the methodology presented in [38], where the development in end-use energy demand is calculated as the product of an activity (e.g. m^2) and an energy indicator (e.g. kWh/m^2y).

There is a large potential for increased energy efficiency in Longyearbyen, particularly for heating. Firstly, the historic and present cost-structure where the residents only pay for heating per square meters and not for actual energy use, gives no incentives to reduce energy consumption. Secondly, more than 50% of the building stock in Longyearbyen was built before 1970 and is not very energy efficient [28]. New buildings must adhere to current building regulations (Norwegian standard TEK17), and we thus assume that new and renovated buildings will cut their specific heat usage from about 500 kWh/m^2y to 150 kWh/m^2y [39]. Due to the assumption of a constant population towards 2050, the total building area stays the same but is replaced by new and renovated buildings at a rate of 2.3% per year [40]. In addition, we assume that energy efficiency in the service sector increases by 1% per year due to the new building regulations [38]. The development of electricity use in the household and service sector is based on development in electricity use per capita in mainland Norway [40]. In the industry sector, the mining activities and the coal-fired power plant itself constitutes 30% of the electricity use in the settlement. Since we assume that in 2030 both the coal-fired power plant is decommissioned and the mining activities are stopped, this leads to a reduction in electricity consumption of 12 GWh, visible as a significant drop in Fig. 3. With these assumptions, the demand for electricity and heat is projected to decrease by 13 GWh and 34 GWh respectively by 2050 (34% and 50%).

Additional energy efficiency improvement may be achieved as a result of the model optimisation. It allows investments in energy efficient equipment including heat pumps, solar thermal collectors and four other energy efficiency measures; energy monitoring, insulation and tightening, technical equipment and energy management (Table S2 in the supplementary material) [38,41].

Since the development in the settlement is highly dependent on political considerations, our energy demand projection represents only one of several possible scenarios for the future of Longyearbyen. We have therefore assessed the sensitivity of the modelling results to the demand projection by testing alternative demand projections (discussed in Section 4.6).

3.3. Solar and wind resources

In this study, we apply hourly solar and wind electricity generation estimates based on renewables.ninja, a web application based on the GSEE model (Global Solar Energy Estimator) [42] and the VWF model (Virtual Wind Farm) [43]. The models use meteorological data from the MERRA reanalysis [44], as well as user-specified data such as the location, hub-height, wind turbine model, orientation and tilt (Tables 1 and 2) as input to produce hourly datasets of solar and wind generation.

Five datasets spanning from 01.01.2000 until 31.12.2018 have been retrieved, representing three possible locations for solar PV and two for wind power in and around Longyearbyen. The specifications of the solar and wind farms and their average capacity factors (the ratio of actual energy generation during a given period to the potential generation if producing at nominal capacity during the same period) are shown in Tables 1 and 2.

The datasets for solar PV generation have been used directly, and their capacity factors are comparable to realised capacity factors on

Table 1
Wind generation data.

Type	Location	Hub height (m)	Turbine size (MW)	Capacity Factor (%)
Onshore	78.2°N, 15.4°E (Platåfjellet)	90	5	26.3
Offshore	78.4°N, 14.7°E (Isfjorden)	119	10	31.9

Table 2
Solar generation data.

Type	Location	Orientation (Azimuth)	Tilt	Avg. Capacity Factor (%)
Ground	78.2°N, 15.4°E (Platåfjellet)	180° (south)	30°[1]	7.67
Rooftop	78.2°N, 15.8°E (Longyearbyen)	315° (northwest)	20°	6.03
Rooftop	78.2°N, 15.8°E (Longyearbyen)	135° (southeast)	20°	7.22

[1] Optimal tilt obtained from the software PVSyst by Thorud [45]. There is no sun during the polar night (March to October), which leads to a low optimal tilt angle close to summer conditions.

already installed residential solar panels in Longyearbyen. Existing solar panels, which were installed in 2013, have exceeded expectations with an annual capacity factor of 7.1% [29]. In TIMES-Longyearbyen, we limit the amount of residential solar installations by estimations of available roof area based on [45].

For wind power, renewables.ninja offers a series of power curves for various wind turbines, but to be able to model newer and bigger turbines, we have used raw wind speed data retrieved from renewables.ninja in combination with power curves of a 5 MW [46] and a 10 MW [47] wind turbine for onshore and offshore applications respectively (Renewables.ninja has recently been updated with additional wind power curves). As a quality control, the MERRA-based wind speed data has been compared to observations from the Norwegian Meteorological Institute from the relevant location Platåberget close to Longyearbyen in the period 03.02.2018 to 31.12.2018 [48], achieving a good fit with the MERRA reanalysis data (correlation coefficient of 0.76).

Fig. 4, which shows the hourly capacity factor for solar and wind through one climatological year (averaged over the 19-year period), indicates that solar and wind could complement each other well in Longyearbyen. The solar resource is strong during the summer months, but not present during the polar night from October until March. Inversely, the wind resource is at its strongest during winter from September to April, but weaker during summer.

3.4. Stochastic modelling approach

Stochastic modelling in TIMES involves taking into account the uncertainty of various input parameters to the system optimisation [49]. This contrasts deterministic model versions, in which the decision-making assumes that all input parameters are certain.

In TIMES-Longyearbyen, we model the short-term uncertainty of seven stochastic parameters, corresponding to electricity generation from solar PV (three possible locations), wind power (onshore and offshore), and the demand of electricity and heat. For this application, it is particularity important to capture the intermittency of solar and wind to ensure energy system robustness. As already mentioned, the solar PV and wind power data are based on Renewables.ninja [42,43], whereas the electricity and heat data are based on real measurements from the power plant in Longyearbyen [32].

A two-stage stochastic model is applied [50,51], and is illustrated by its scenario tree in Fig. 5. Here, the first stage involves investment decisions made over the whole modelling horizon based on the expected outcome of the operational scenarios but without knowing their true realisations. This is a key property of the approach, as the investments are not only optimised for one set of load profiles and renewable generation profiles, but take into account a wide range of possible outcomes. This leads to a set of investments that are feasible and identical for all sixty operational scenarios, important for e.g. security of supply. The true outcome of the operational scenarios is first revealed in the second stage, where operational decisions are made across all scenarios and periods. Each branch in the second stage corresponds to

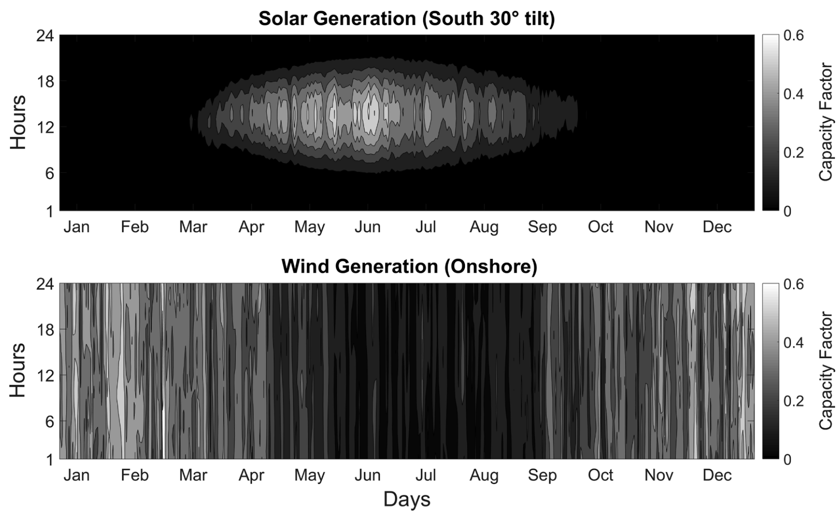

Fig. 4. Solar and wind resources.

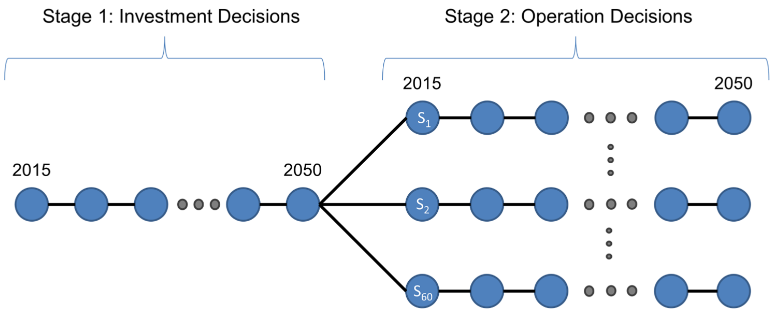

Fig. 5. Illustration of a two-stage scenario tree with sixty operational scenarios (adapted from [53]).

one operational scenario, corresponding to different realisations of the stochastic parameters, all with the same probability of occurrence. We employ a multi-horizon structure [51], in which investment and operational decisions are made simultaneously, and which assumes no dependency of operational decisions between model periods. This means there is no learning effect from observing operational scenarios, which significantly reduces model size, and is also a good approximation of real decision processes since including such learning effects would be similar to assuming perfect foresight of operational outcomes over the modelling horizon [52].

In TIMES-Longyearbyen, we use sixty operational scenarios to describe our stochastic parameters. Increasing the number of scenarios can improve the robustness of the results, but leads to increased computational effort [54]. The sixty scenarios play an important role in the stochastic modelling approach, as they should reflect the variability of the parameters and in addition represent realistic operational situations. The scenarios are selected from historic datasets through a method that combines two techniques called random sampling and moment matching, based on [22]. This involves:

(1) Random sampling of historical days to construct 60 independent scenarios, where each scenario follows the temporal structure of the model and consists of two sampled days with hourly resolution per season (192 time-slices). The approach gives consistent daily correlations by sampling consecutive hourly values throughout the day, and correlations between the seven uncertain parameters by sampling concurrent days. We sample the days separately for each of the four seasons, assuming no seasonal dependency, and repeat the procedure for each investment period thus also capturing interannual variability. A set of scenarios consists of 60 independent scenarios * 24 h * 2 days * 4 seasons * 9 periods * 7 stochastic parameters = 725 760 values.
(2) Repeating this procedure to generate a large amount of possible scenario sets, in this case 10 000 sets.
(3) Calculating the first four moments (mean, variance, skewness and kurtosis) for the historic data and for each of the 10 000 scenario sets.
(4) Finding the deviation of the first four moments of each scenario set to the historical datasets, and select the set of scenarios with the lowest deviation and thus the best fit with the statistical properties of the original datasets.

Fig. S9 in the supplementary materials presents a comparison of the mean, variance, skewness and kurtosis profiles of the selected stochastic scenarios and the historical datasets. The figures show that by following the scenario generation method we achieve a reasonable approximation to the historic data. Furthermore, Fig. S10 in the Supplementary Materials compares the probability density functions of onshore wind and solar PV generation, showing that our model captures their intermittent power generation sufficiently well.

Fig. 6 below illustrates the difference between a deterministic and a stochastic modelling approach. The deterministic profiles are based on the expected value of each parameter, while the sixty stochastic scenarios are selected by the scenario generation method explained in the previous paragraphs. The figure shows a day of solar generation during summer, as well as onshore wind, electricity demand and heat demand during a winter weekday. These days are chosen since generation and consumption are highest during these respective seasons and days. Fig. 6 clearly shows the extra variability modelled in a stochastic approach, with periods of both low and high generation from variable renewables and periods of varying heat and electricity demand. The ability of the energy system to support these realistic operational situations is important for security of supply in the settlement.

3.5. Model cases

We investigate four model cases, each distinguished either by their modelling approach or by constraints that allow us to study specific cases for Longyearbyen's future energy system. All input parameters, such as future technology costs, efficiencies, fuel costs and so on are equal in all model cases. We also assume, in all cases, that the existing coal-fired power plant is decommissioned within ten years from now, so that by 2030 an entirely new energy system will be in place in Longyearbyen. The four model cases are summarised in Table 3 below.

The first model case, *DET*, is a deterministic model version constrained to use only renewable energy sources, either locally available or through imported hydrogen produced elsewhere, presumably in mainland Norway and shipped to Longyearbyen. Its main purpose is to illustrate the difference between a deterministic and a stochastic model version, and to assess and compare the different investment strategies in the two approaches. The DET case is not considered a realistic optimisation of Longyearbyen's future.

The second case, *ISO*, is a stochastic model that constrains all import processes to the island, resulting in a completely isolated energy system that has to draw all its power and heat from locally available renewable energy resources.

The third case, *HYD*, is a stochastic model that allows importing hydrogen from mainland Norway. We also assume that the hydrogen is produced by electrolysis using surplus Norwegian hydro- or wind power rather than steam reformation of natural gas, and thus considered 100% renewable. The cost of importing hydrogen has been set to 35 NOK/kg H_2 [55]. Due to the uncertainty surrounding this future price, the sensitivity of the model results to the hydrogen price has been assessed.

The fourth case, *FOS*, is a stochastic model that permits import of fossil fuels (diesel and/or natural gas) in addition to hydrogen. This has the potential to reduce the storage requirements, help stabilise the grid and reduce the total cost of the system. In addition, if only or primarily used as back-up generation, it would lead to limited amounts of

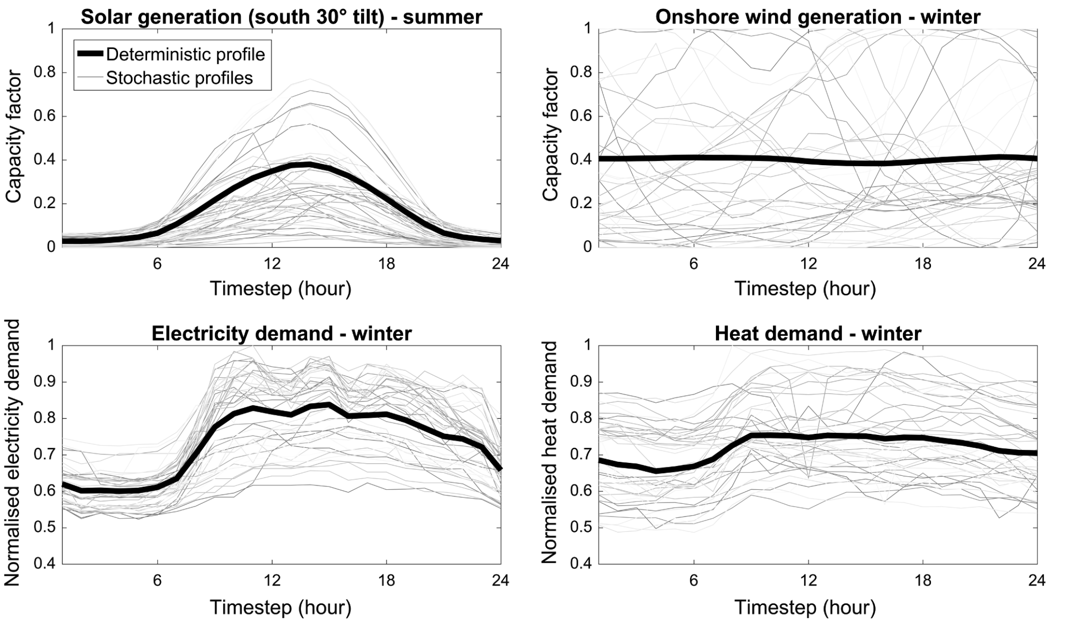

Fig. 6. Deterministic and stochastic daily profiles of hourly capacity factors for solar generation during summer, as well as onshore wind generation, electricity demand, and heat demand during a winter weekday. The thick bold line refers to the daily profile used in a conventional deterministic model, whereas the thin lines in grey are the sixty stochastic profiles selected by the scenario generation method.

Table 3
Model Cases investigated in the study.

Model Cases	Method	Description
DET	Det.	Unrealistic case, included in order to compare model techniques
ISO	Stoch.	Isolated system
HYD	Stoch.	Allowing imports of renewable hydrogen from mainland Norway
FOS	Stoch.	No constraints, i.e. allowing also imports of fossil fuels

greenhouse gas emissions. In the final analysis, we run several additional cases each with a pre-determined maximum level of CO_2 emissions in Longyearbyen exploring options ranging from *HYD* to *FOS*.

4. Results and discussion

4.1. Deterministic (DET) versus stochastic modelling approach

A conventional deterministic modelling approach, which considers only one operational scenario in its optimisation, can give valuable insights, but in this particular case study it could lead to misleading results.

The *DET* model case gives investments in a system heavily reliant on wind power, supplemented by solar power and batteries to smoothen intraday variability (Fig. 10). Heating is largely electrified, and is generated through electric boilers as well as geothermal and seawater based heat pumps. The electrification requires additional electricity, which also plays a part in increasing the required installed electricity generation capacity. In addition, the model decides to invest in energy monitoring, the cheapest alternative of the modelled energy efficiency measures.

As illustrated in Fig. 6, the solar and wind resources in the *DET* model case are based on their climatological features and give an inaccurate description of their true variability. This consequently leads to an overestimation of the contribution of wind power in the model, with wind unrealistically treated as a base-load generator. The case clearly demonstrates that using a deterministic modelling approach could lead to misleading results when variable renewables become a major fraction of installed capacity.

The lack of realism in the *DET* model case is further evidenced by testing the value of stochastic solution (VSS), a test that aims to evaluate the advantage of using a stochastic model version versus a deterministic one [22,56]. It works by fixing the first-stage decisions in the deterministic model (the investments), and thereafter solving the model using the stochastic operational scenarios. In other words, we use the system typology that the deterministic model version invests in, and test it for the sixty operational scenarios in the stochastic model with no additional investments allowed. Applying the VSS to the *DET* model case results in an infeasible model run. This indicates that the system is not able to cover the demand in at least one of the operational scenarios. The reason for this is the overestimation of the contribution from wind energy in the deterministic version, which leads to insufficient investments in reserve capacity making the energy system unable to meet the demand in operational scenarios with e.g. unfavourable wind and solar availability and/or high electricity and heat demand. This shows the importance of having an adequate representation of short-term solar and wind variability.

The question remains whether our stochastic approach is sufficiently robust to deal with long term persistence of the solar and wind resources, in particular extended periods of low supply. Tsekouras and Koutsoyannis [24] have shown that a significantly positive autocorrelation (Hurst coefficient of 0.84) characterizes long time series of wind and solar radiation in Europe. Zeyringer et al. [57] in a study of the UK, used a high resolution model softly coupled to a TIMES based energy system model to explicitly model impacts of interannual variability of weather. Our approach, based on [22], has the benefit of preserving computational efficiency while allowing for a combined

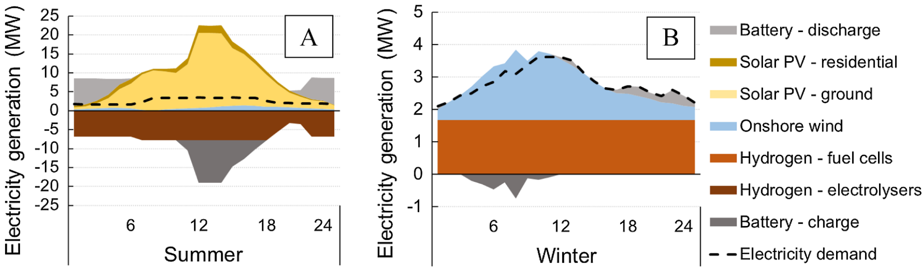

Fig. 7. Examples of system operation in 2050 for a summer (A) and winter (B) day. Note the different scales for electricity generation in A and B.

stochastic treatment of both supply and demand. Inspection of the energy system configurations which emerge as results of the stochastic modelling of Longyearbyen in the present study, see Sections 4.2–4.5, convinces us that they have sufficient energy storage to be robust against periods with persistent low solar or wind resources. However, a more sophisticated treatment of the statistical properties of solar and wind data (e.g. [58]) could be interesting for further development of the model for wider applicability.

4.2. An isolated system (ISO)

The *ISO* case considers a completely isolated Longyearbyen, powered only by locally available renewable energy resources after 2030. By following a stochastic modelling approach, the model finds the optimal system configuration that is able to meet the demand of heat and electricity in all sixty operational scenarios modelled, even those with unfavourable wind and solar conditions.

Large installed capacities of solar and wind as well as a full hydrogen value chain with both short- and long-term energy storage is necessary for a robust and reliable isolated energy system. Fig. 7 shows two examples of system operation in 2050 during a summer day (A) and a winter day (B), which illustrate well the trend seen across the operational scenarios. Detailed results for each scenario is found in Fig. S6 in the supplementary materials.

The fall and winter seasons are important design factors in all model cases, but particularly in the *ISO* case. Due to colder temperatures the demand of heat and electricity are higher during these seasons, the polar night means there is no contribution from solar PV, and although the wind resource is generally higher during fall and winter, there are periods with little or no wind generation. To cover such periods, shown in Fig. 7B, the model uses seasonally stored hydrogen produced in periods of excess electricity (Fig. 7A). The model invests in large amounts of hydrogen storage (31 GWh in 2030 and 22 GWh in 2050), which in addition to covering the demand also needs to compensate for boil-off losses during long-term storage and losses in the fuel cells.

The need for producing and storing large amounts of hydrogen with a relatively low round-trip efficiency, the electrification of heating, and relatively low capacity factors compared to dispatchable technologies call for a large installed capacity of solar and wind. In 2030, the model has invested in 119 MW of solar PV capacity and 126 MW of onshore wind, corresponding to a total capacity of variable renewables ~50 times larger than the peak hourly electricity demand. This leads to periods with large amounts of excess electricity generation. Fig. 7A shows an example of how otherwise curtailed electricity is used in electrolysers for hydrogen production, to be stored for use in other seasons. Here batteries also play a useful role. The model decides to invest in ~10 MW of li-ion battery charging/discharging capacity and ~57 MWh of energy storage in 2030 (~11 MW and ~51 MWh in 2050). In Fig. 7A, one can see that batteries are not only useful for intra-day balancing of demand and supply, but also for balancing the electrolyser loads. By storing a large part of the solar peak in the middle of the day and distributing it to the night, the batteries help the electrolysers to work with a more stable load and avoids investments in large electrolyser capacities otherwise necessary to cover the solar peaks.

In the *ISO* case, all four energy efficiency measures (presented in Section 3.2) are fully implemented, reducing the annual demand of electricity and heat by about 10%. Due to the additional infrastructure needed for power generation, investing in energy efficiency measures is found to be economically attractive in this model case.

Introducing large fractions of variable renewables into a small isolated system could lead to challenges in maintaining grid stability [59–61]. Grid support services traditionally offered by fossil-based technologies, such as frequency and voltage regulation, fault-ride-through and spinning reserve must in this case be supplied through the power electronics of renewables, hydrogen fuel cells and by energy storage technologies. Introducing demand response or installing reserve fossil fuel generators could further help maintain stability in the system. Building such a system could spur further research on its detailed operation.

4.3. Hydrogen import (HYD)

The high investments in storage and generating capacity seen in the *ISO* case would be costly (Fig. 11). This motivates the *HYD* case, which allows import of hydrogen from mainland Norway. The Norwegian power system is characterised by large amounts of hydropower (96% of electricity generation), and has a surplus of about 15 TWh in a normal hydrological year [62]. Utilizing the flexibility of the Norwegian power system, which is many times larger than the Longyearbyen system, could reduce the infrastructure for local power and hydrogen production compared to the *ISO* case. Under the assumption that the imported hydrogen is produced from electrolysis powered by surplus renewable electricity and transported by ship fuelled by hydrogen this model case could still be considered 100% renewable. The amount of imported hydrogen, averaged across all scenarios, is found to be 89 GWh and 60 GWh in 2030 and 2050 respectively. Scenario-specific results for the HYD case are presented in supplementary materials S7.

The 35 NOK/kg import price used in this study [55] is assumed to bear the costs of producing hydrogen in mainland Norway and the transportation to Longyearbyen. Due to the uncertainty associated with this price, we have assessed the sensitivity of the energy system architecture and total system cost by additional model runs with results displayed in Fig. 8. As expected, the amount of imported hydrogen depends strongly on its price. For a price lower than 70 NOK/kg, all of the required hydrogen is imported. For a price of 70 NOK/kg and higher, an increasing share of local hydrogen production is found economically attractive, but at the same time the total share of energy generation from hydrogen fuel cells decreases while wind and solar increase. Producing all hydrogen locally becomes economical only at a very high import price (as shown in Fig. 8). At this point, the HYD case becomes identical to the ISO case. However, a future hydrogen price this high seems very unlikely. Glenk and Reichelstein [63] found a

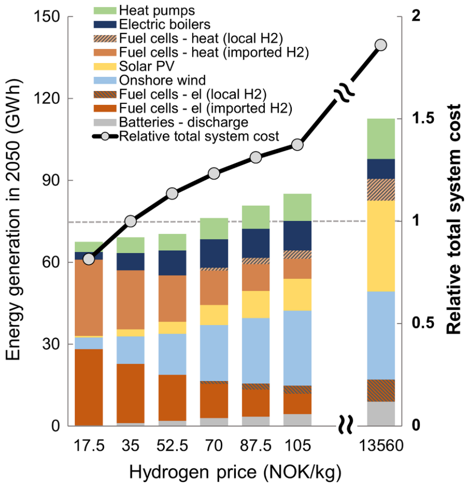

Fig. 8. Sensitivity of energy generation in 2050 (bars) and total system cost relative to a hydrogen price of 35 NOK/kg (line) to the cost of hydrogen.

current break-even price for renewable hydrogen through electrolysis in Germany of 3.23 €/kg (~32 NOK/kg), and predicted a decrease to ~2.3 €/kg (~22 NOK/kg) by 2030.

4.4. Fossil fuels (FOS)

Allowing use of fossil fuels could further reduce the costs of Longyearbyen's future energy system. For a system with no emission restrictions, the model shows a preference towards fossil fuels, investing in new diesel generators, gas cogeneration turbines, pure gas turbines and gas boilers (Fig. 10).

In the unrestricted *FOS* case, moving from coal to natural gas, diesel, and some renewable capacity reduces the CO_2 emissions with a factor of 2/3 from 2015 to about 20 000 ton CO_2 annually from 2030. Fig. 9 shows how the total system cost, and the share of renewables in final energy demand varies with a constraint on CO_2 emissions ranging from no regulations (corresponding to the *FOS* case) to zero emissions (corresponding to the *HYD* case). The system cost first rises gradually as emissions are beginning to be constrained, before increasing rapidly to reduce the last tons of CO_2. This shows that achieving some emission

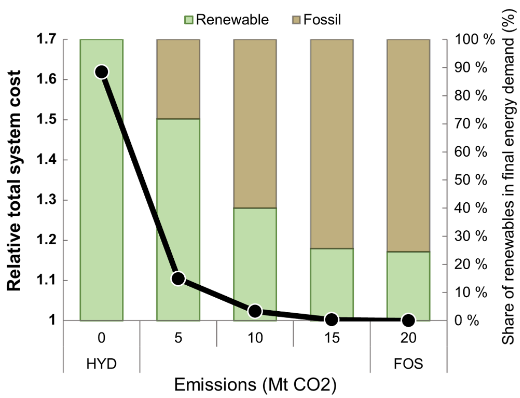

Fig. 9. The impact of constraining emissions on the total system cost and system composition.

reductions is relatively cheap, whereas the last tonnes of CO_2 are very costly to remove.

Allowing for some, but minor emissions could thus be an effective way of considerably reducing the total system cost, and at the same time increase redundancy and possibly reduce local environmental impacts such as land-use and visual impact from large wind turbine installations. As an example, allowing for 25% of CO_2 emissions compared to an unrestricted case (*FOS*) annually would only give about 10% higher total system cost.

4.5. Summary of key results

This section summarises key results on the energy system structure and costs for the four investigated model cases. Tables with detailed results on installed capacity and energy generation as well as scenario specific figures can be found in the supplementary material to this paper.

Fig. 10 shows a comparison of the installed capacities in the *ISO*, *HYD* and *FOS* cases in 2030 and 2050 compared to today's existing capacity. Although the model optimisation suggests investment in new infrastructure already in 2020, it decides to keep the coal-fired power plant until decommission in 2030 in all cases, adding only some minor investments in energy efficiency measures and onshore wind capacity. Since the system composition also does not change much between 2030 and 2050, we only show the installed capacities in 2030 and 2050 in Fig. 10 (complete results are available in the supplementary material).

Electrification of heating is seen in all model cases. Electric boilers, heat pumps and heat from hydrogen fuel cells become the main source for heating in all but the *FOS* model case, where gas boilers provide the majority of heat to the settlement. Large investments in onshore wind are also seen in all model cases. These results are consistent with the Grimsey island study [1], which included fewer options, but also showed that wind and hydrogen could be important parts of Arctic energy systems.

Due to faster cost reductions for solar PV technologies than for wind and despite its lower annual capacity factor, one can see that the share of solar PV in the generation mix increases from 2030 to 2050 in all model cases.

Fig. 10 also shows the total installed capacity of all model cases. As expected, this is very high in the *ISO* case, about seven times larger than the current installed capacity. In all other cases, the total installed capacity is comparable to today's level, as these cases rely on fossil fuels or import of hydrogen.

Since the coal-fired power plant is kept until 2030 in all model cases, this leads to more similar annual system costs between cases for the entire period 2015–2050 than for the period 2030–2050. As the energy system costs are discounted back to 2015, earlier costs play a more important role in the optimisation with respect to total costs than later ones. This explains why the total discounted system costs (Table 4) are more similar in comparison to the large differences seen in the average annual system costs between 2030 and 2050 (Fig. 11).

In Fig. 11, one can see that the *ISO* case has the highest average annual costs, about three times larger than the *HYD* case and about ten times larger than the *FOS* case. This is due to the high requirements for renewable energy capacity, storage and hydrogen infrastructure in an isolated system, which also leads to a very capital-intensive system, where ~84% of the annual costs in 2050 are related to investments. In the *HYD* and *FOS* cases, on the other hand, imports of energy carriers are the driving cost factors, corresponding to ~60% and ~50% of mean annual costs respectively.

The average cost of energy (reflecting both electricity and heat) shown in Table 4 is calculated between 2030 and 2050, thus only taking into account the new energy system in each model case, consistently with Fig. 11. We see that moving from the unconstrained *FOS* case to the 100% renewable *HYD* case almost quadruples the cost of energy, but constraining 2050 emissions to 5000 tonne CO_2/year (~25% of the

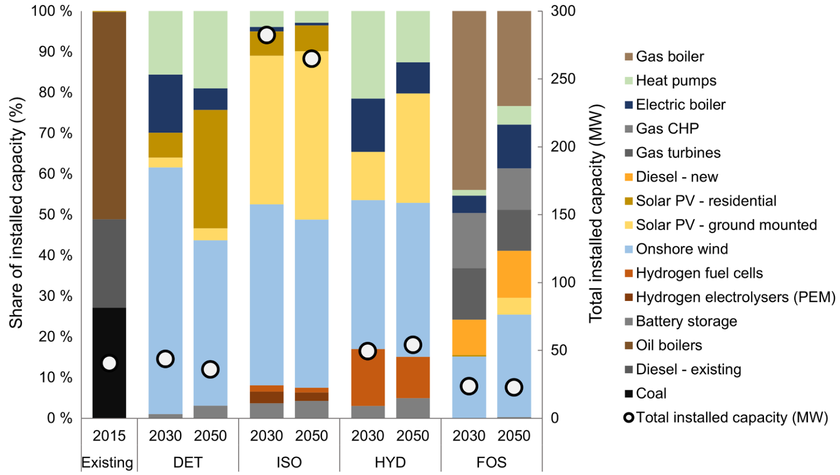

Fig. 10. Share of (bars) and total (markers) installed capacity in all cases. See Table S4 in the supplementary materials for detailed results on installed capacity for all investment periods.

unconstrained 2050 emissions and less than 10% of 2015 emissions) increase the average cost of energy for 2030–2050 by ~50%.

Even though our model has a relatively high temporal resolution in comparison to other TIMES models, it is worthwhile to validate the model against a less scaled down model. In order to do so, we developed another model version with 672 time-slices, modelling one full week with hourly resolution per season. These two models are essentially equal, with the only difference being the temporal resolution. In order to maintain computational feasibility, we had to reduce the number of stochastic scenarios from 60 to 15. In addition, the scenario generation method selects a full week instead of individual days. We tested the new model with our three main model cases (ISO, HYD and FOS), achieving consistent results in comparison to our 192 time-slice model. When comparing the value of the objective function, the total system cost, all model cases results in a slightly lower total system cost in the 672 time-slice model in comparison to the 192 time-slice model. The HYD scenario has the highest deviation with 5.9%, whereas the ISO case and the FOS case deviates 4.2% and 1.1% respectively. Furthermore, the overall system composition stays the same in both model cases, showing that our scaled down model has an adequate temporal resolution.

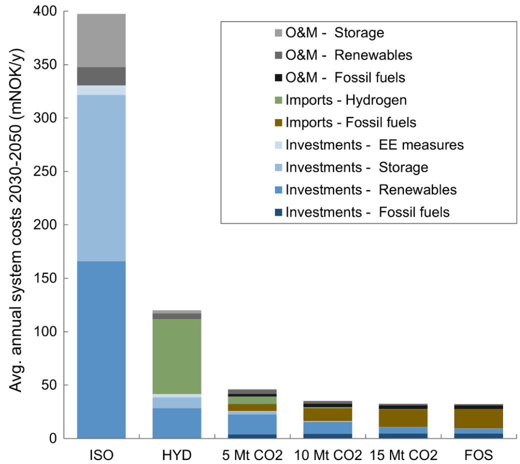

Fig. 11. Avg. annual system cost between 2030 and 2050.

4.6. The role of policy and regulations

Our modelling results suggest that a future energy system in Longyearbyen based primarily on renewable energy sources is feasible, reliable and achievable. Energy efficiency plays an important role, and is a crucial part of our demand projection (hereafter denoted *base*). We envision drastic improvements of energy efficiency in buildings as well as reduced electricity demand due to changes in the industry sector. The demand projection is based on a number of assumptions. If policies fail to address energy efficiency, it could have a great impact on the size and cost of the new required energy infrastructure in Longyearbyen.

To assess the sensitivity of our results, we have investigated the impact of alternative demand projections (shown in Fig. 12). The *status-quo* demand projection assumes no measures are incorporated to reduce energy demand, leaving the demand of heat and electricity on today's level (~70 GWh heat and ~40 GWh electricity) until 2050. The *high* demand projection is a more aggressive demand projection, which assumes a doubling of energy demand towards 2050 (~140 GWh heat and ~80 GWh electricity). For heat, this would mean a continuation of the trend seen between 2000 and 2010 (continuous line in Fig. 3). This would be consistent with a doubling of the population to about 4000 residents in 2050 and assuming that the specific heat demand (kWh/m^2 y) remains on today's levels. In addition, it assumes an increase in

Table 4
Key economic results.

Key economic results	ISO	HYD	5 Mt CO_2	10 Mt CO_2	15 Mt CO_2	FOS
Total discounted system cost (bNOK)	4.93	2.21	1.51	1.40	1.37	1.36
Cost of energy (2030–2050 avg.) (NOK/kWh)	5.73	1.73	0.67	0.51	0.47	0.46

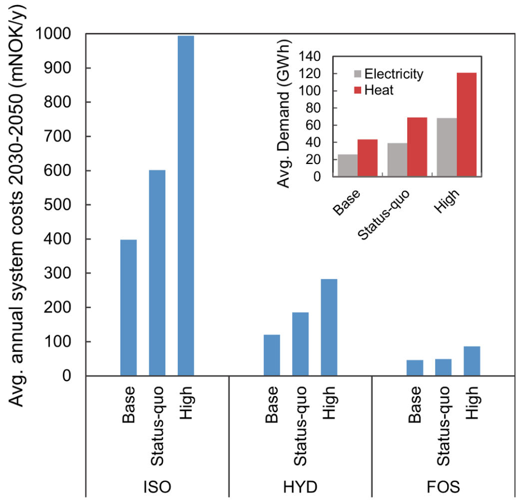

Fig. 12. Sensitivity of annual system cost in 2050 to alternative demand projections. The average energy demand (electricity and heat) between 2030 and 2050 for the alternative demand projections is shown in the fig. inset.

activities e.g. within tourism and/or research, as well as a large degree of electrification (e.g. of the transport sector) that leads to a doubling of the electricity demand. A projection with significantly lower future energy demand than the *base* scenario is not considered realistic and therefore not assessed.

Fig. 12 shows that an increase in energy demand gives significantly more expensive systems in all model cases. The *ISO* case is the most sensitive to changes in energy demand, linearly increasing its annual system cost by 3.7 mNOK per GWh of increased energy demand. This is expected due to the extra infrastructure needed to cover the higher energy demand. The *HYD* and *FOS* cases are less sensitive to changes in the demand, due to the availability of imports of energy carriers, and have an increase in annual system costs of only 1.0 and 0.3 mNOK per GWh respectively.

The selection of discount rate is expected to influence particularly the balance between capital and operation intensive technologies. We have tested all cases with a 2% and 6% discount rate in addition to the base case 4%. The results displayed in Fig. 13, show that these changes of discount rate have a discernible but not drastic impact on the results for Longyearbyen. The overall composition of the system stays roughly the same in all model cases, although a discount rate of 2% favours investments in renewable capacity (high upfront investment, but low operational costs), while a 6% discount rate favours investments in fossil fuels or imported hydrogen (lower investments, but higher running costs).

An advantage of a renewable based system is its modularity, which means that one can incorporate units into the system one at a time. This can help sizing the system according to the actual development of a highly uncertain future energy demand. Furthermore, a gradual transition to a system based on renewables, while phasing out the coal-fired power plant in a controlled manner, could ease the operation and keep security of supply in place. Modularity also improves system reliability, as it is highly unlikely that several units fail at the same time.

For future work, the TIMES model of the settlement could be expanded to also include the transportation sector. There are almost as many snowmobiles as people and about 1500 cars in the settlement [37]. Tourism is likely to lead to an increased use of tourist ships and visits from large cruise ships. This puts sustainable tourism on the agenda. Given energy demand projections for these sectors, an expanded version of the present model could evaluate the potential of electrification and the use of hydrogen in the transport sector, enabling cross-sector synergies and potentially deeper decarbonisation of the settlement.

Environmental aspects not captured by this modelling study should be included in planning and policy making. As an example, the installation of new infrastructure, e.g. onshore wind turbines and extensive areas for solar panels, can disturb existing habitats in an already constrained Arctic ecosystem and their impact should be carefully considered before installation. The broader environmental impact of lithium ion batteries should also be further assessed. Not only in terms of greenhouse gas emissions and energy use in the production phase, but also in terms of lifecycle impacts including materials usage, toxicity and the social risk particularly related to the mining of cobalt [64,65].

We recommend that new policies ensure that energy efficiency is prioritised, and that a new system should include renewable generating capacity, energy storage, electrification of heating, and imports of hydrogen, in this case most likely from mainland Norway. Fossil fuel backup capacity could be installed to reduce costs and increase security of supply in the settlement. A renewable based energy system in an Arctic location such as Longyearbyen could also be a valuable research

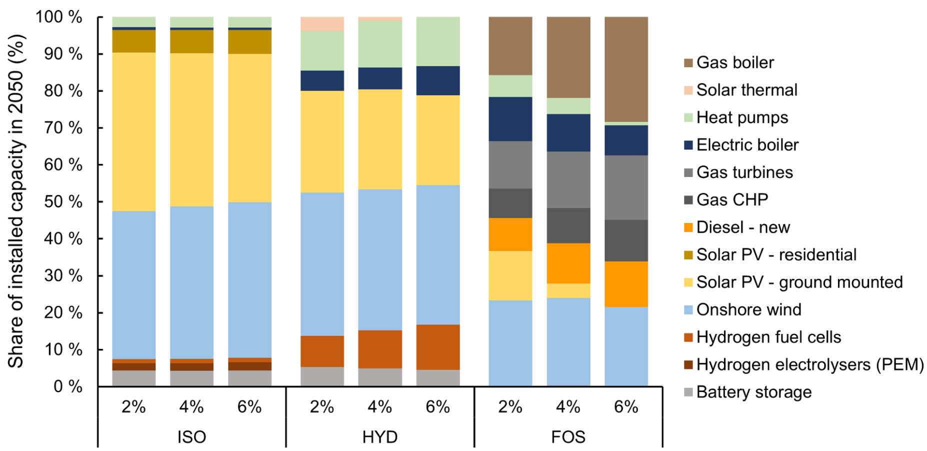

Fig. 13. Sensitivity of the key model results on the discount rate.

opportunity, and an example for others to follow.

The approach and the findings from this study should be relevant for other Arctic communities. Although wind and solar resources vary from place to place and are likely to influence the structure of the resulting optimal energy system, most of the properties of the energy system components studied here should be almost directly applicable to studies of other locations.

5. Conclusion

Three main conclusions can be drawn from this work. First, incorporating an adequate modelling of the variability of renewables is highly important for ensuring the robustness of modelling studies in cases where a significant part of the energy supply is based on variable renewables. Handling this variability is particularly important when security of supply is of highest importance, such as in the case of a remote Arctic settlement. A careful representation of the stochastic properties of the solar and wind resources is recommended.

Second, the detailed and realistic case study shows that Longyearbyen has the potential of being supplied by an energy system based primarily on renewable energy sources with wind and solar as both complementary and critical contributors. The potential of harnessing wind and solar in Arctic locations is significant, and when utilised together they have beneficial complementary properties. Energy efficiency is also of high importance, and policies and regulations should be directed towards improving energy efficiency and reducing energy usage. An isolated system based only on locally available renewable resources is technically feasible, but requires high installed capacities, and is found to have annual system costs about three times larger than a case where import of hydrogen is allowed. Allowing for a limited fraction of the energy supply to come from fossil fuel use could significantly reduce system costs, increase robustness and system reliability while still obtaining major reductions of emissions compared to cases where the use of fossil fuels is unconstrained.

Finally, the developed model tool could easily be expanded to optimise an extended energy system, which not only supplies the settlement, but also tourist ships and other transportation needs. It could also be adapted to other remote settlements with other starting and boundary conditions. While specifics including costs of hydrogen import can be expected to vary with location, one may speculate that the major building blocks of the emerging system including wind, solar and hydrogen storage will remain. These technologies in contrast to geothermal and carbon storage have the advantage of being generic and not so dependent on costly investigations of local conditions.

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The motivation to conduct this study came after a summer course on Sustainable Arctic Energy Exploration and Development at the University Centre in Svalbard. This course included a group project led by the first author of the present study, where a simple conventional deterministic TIMES-model of the energy system in Longyearbyen was developed and analysed. The results from this group work (also partly reported in [66;67]) indicated that a system based mainly on solar and wind in combination with batteries could be a reliable and cost-effective solution. In order to set these early results on a firm basis, a more detailed modelling study was required.

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Declaration of Competing Interest

The authors have no competing interests to declare.

Data accessibility

Solar and wind data used in this this study are publicly available and can be retrieved from https://www.renewables.ninja/. Costs and technological parameters used as input to the model are given in the supplemental materials (Table S1).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2019.114079.

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Paper III

6.3 Short-term solar and wind variability in long-term energy system models - a European case study

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Short-term solar and wind variability in long-term energy system models - a European case study

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Abstract

Integration of variable renewables such as solar and wind has grown at an unprecedented pace in Europe over the past two decades. As the share of solar and wind rises, it becomes increasingly important for long-term energy system models to adequately represent their short-term variability. This paper uses a long-term TIMES model of the European power and district heat sectors towards 2050 to explore how stochastic modelling of short-term solar and wind variability as well as different temporal resolutions influence the model performance. Using a stochastic model with 48 time-slices as benchmark, our results show that deterministic models with low temporal resolution give a 15-20% underestimation of annual costs, an overestimation of the contribution of variable renewables (13-15% of total electricity generation) and a lack of system flexibility. The results of the deterministic models converge towards the stochastic solution when the temporal resolution is increased, but even with 2016 time-slices, the need for flexibility is underestimated. In addition, the deterministic model with 2016 time-slices takes 30 times longer to solve than the stochastic model with 48 time-slices. Based on our findings, a stochastic approach is recommended for long-term studies of energy systems with large shares of variable renewable energy sources.

Keywords: Energy modelling, TIMES energy-models, variable renewable energy, stochastic modelling

1 Introduction

The European power sector has the potential of becoming nearly carbon neutral by 2050 through increasing the share of renewable energy in the electricity mix [1]. A major share of this increase is expected to come from solar and wind technologies. Over the past two decades, solar and wind have experienced massive cost reductions and technological development. In many locations, unsubsidised solar and wind are already cheaper than their fossil-fuelled counterparts, and costs are projected to plummet further [2]. However, due to their variable and partially unpredictable nature, a large share of solar and wind in the electricity mix gives rise to a number of challenges, ranging from short-term systems operations to strategic planning on a long-term timescale [3].

Long-term energy models are frequently used to aid policy-making, for strategic planning, and to understand the future complexity of the energy system. Such models have the advantage that they are capable of modelling the entire or parts of the energy system several decades into the future, but they often model short-term operations in a stylized and simplified way [4]. When energy modelling started gaining popularity after the oil crisis in 1973 [5], the major source of variability in the energy system was on the demand side [6]. Models where thus developed to treat the relatively regular diurnal and seasonal fluctuations of the load curve while maintaining computational efficiency [7]. Consequently, this led to models generally having a low number of time-slices [8, 9].

Merrick [6] found that a year of hourly electricity demand could be sufficiently represented using only ten data points, while the joint profiles of wind, solar and electricity demand require in the order of 1000 data points to be fully represented. Due to the low temporal resolution of many traditional long-term energy models, they might not be well suited for exposing and addressing the challenges of tomorrow's energy system. This is also pointed out by Pfenninger et al. [7], who refer to "resolving time and space" as one of four main challenges energy system models face today. It has also been shown that failing to take into account the short-term fluctuations of solar and wind could potentially give biased model results, overestimate the contribution from variable renewables (VRES), and underestimate costs or greenhouse gas emissions [10–14]. As the share of VRES in the power system grows, the representation of their short-term variability thus becomes increasingly important in such models, with a large impact on long-term strategic planning.

Improving the representation of short-term variations of solar and wind in long-term energy models have seen increased attention in recent years. Collins et al. [15] thoroughly reviewed the challenges of long-term energy models when dealing with variable solar and wind, and state-of-the-art methodologies to address them. This includes soft-linking long-term energy models with operational power system models, increasing or improving the temporal resolution and improving the technical representation.

Welsch et al. [10] compared three models of the Irish power sector; a long-term energy model (OSeMOSYS) with 12 time-slices, an enhanced OSeMOSYS model with technical constraints, and a soft-linked TIMES-PLEXOS model with 8784 time-slices. Their results showed that the simple OSeMOSYS model underestimated the need of flexibility in the system and overestimated the effective use of wind energy. By adding operational constraints, the enhanced OSeMOSYS model was able to adequately reproduce the results of the soft-linked TIMES-PLEXOS model. As an alternative to soft-linking, in which the models follow an iterative approach where results are fed from one model into the next run of the other, one could also hard-link models to get one integrated model [16, 17]. Poncelet et al. [11], compared a TIMES long-term energy model of Belgium to a merit-order model and the unit commitment model LUSYM. Here, the authors conclude that for a high penetration of variable renewables, improving the temporal representation is more important than including detailed techno-economic operational constraints to the model.

Much of recent work has focused on improving the temporal representation in long-term energy models. One method is to simply increase the temporal resolution by incorporating more time-slices, e.g. by modelling representative days with hourly resolution or including more representative days [18, 19]. Kannan & Turton [19] increased the temporal resolution of a Swiss TIMES model from 8 (two diurnal time-slices per season) to 288 time-slices (24 h x 3 days x 4 seasons), achieving what they referred to as "a far better solution" in the more detailed model. TIMES-Norway [20] uses 260 times slices annually in order to give a detailed description of the Norwegian hydropower system.

Another recently active area of research has been the method of selecting representative days or time-slices, including the use of heuristic methods, random sampling, clustering or even optimisation methods [21–25]. Pfenninger [26] compared various methods in a model of the Great Britain power system using the open-source modelling framework Calliope. By applying downsampling, heuristics and clustering techniques, Pfenninger showed that the results varied strongly with the chosen method, particularly with large shares of variable renewables. Heuristics showed promise, but the best method depends strongly on the type of system studied, the input data and the model setup. Furthermore, Hilbers et al. [27] presented an approach for sampling time-series based on the estimated importance of each time-step and then including a number of the most important time-slices in their model. In an idealised model of the UK power system, they showed that their method performed better in comparison to using random sampling, k-medoids clustering or the use of individual years.

Many authors have looked at the impact of improving the technical representation of long-term energy models. This includes adding operational constraints to the model, specifying e.g. minimum load levels, ramp-rates, start-up times etc. [28, 29]. Another approach is to incorporate modelling of operating reserves (ancillary services), as in [30]. Gaur et al. [29] added a unit commitment (UC) extension to a TIMES model of the Northern regional grid of the Indian power sector. They found that adding operational constraints helped to avoid an overestimation of VRES penetration and a better estimation of the needs for flexible generation.

Stochastic modelling has in recent years emerged as an effective way of representing short-term uncertainty in long-term energy models [31–35]. While traditional deterministic models make decisions with perfect foresight of solar and wind availability, a stochastic model can take into account their short-term uncertainty in the optimisation (see section 2.5.3). Seljom and Tomasgard [31] showed that a stochastic representation of short-term wind generation resulted in lower energy system costs, lower wind power investments, less electricity exports and an increased use of biomass compared to a deterministic model. As a result, they recommended that decision makers use a stochastic approach in order to obtain more solid results. Nagl et al. [36] developed a stochastic optimisation model for the European electricity system. Through comparing the results from their stochastic model to one with a deterministic investment strategy, they found that VRES were significantly overvalued in the deterministic model version, leading to a an underestimation of costs and flexibility requirements. EMPIRE is another example of a stochastic model of the European electricity system [34], used for example to study the role of demand response in Europe [37].

In this work, we evaluate and demonstrate different modelling approaches on how to represent the short-term variability of solar and wind generation in a long-term TIMES energy model of the European power and district heating systems. This includes exploring the influence of both modelling approaches to consider uncertainty and different temporal resolutions on model results. To do so, we have developed and applied TIMES-Europe, a least-cost optimisation model of the European power and district heat sectors. Five model versions have been developed, all fundamentally identical but each with increasing temporal resolution. Each of these versions were further modelled using a conventional deterministic approach and a stochastic approach that takes into account the uncertainty of short-term solar and wind variability as well as the electricity demand.

Most previous studies that have investigated the importance of representing short-term solar and wind in long-term energy models focus on national energy systems, e.g. [10, 11, 26, 27]. To the authors knowledge, this paper is the first to assess the effect of a varying temporal resolution and modelling methodologies on a European scale. As the European power grid is becoming more and more harmonised, capturing the dynamics of cross country trade and the correlation of solar, wind and electricity demand across the whole of Europe is becoming increasingly important.

In addition, we explicitly compare the performance of stochastic versus high-resolution deterministic modeling approaches using TIMES at the European level. We believe this study is the first to assess how fine resolution a deterministic model must have in order to perform approximately as well as a benchmark stochastic model.

A third contribution is the application of a TIMES long-term energy model to a realistic case-study of the European power and district heat systems towards 2050. We expect there will be a demand for a range of similar studies in the future, e.g. to take into account policy constraints and looking at how energy storage and grid interconnections can help to accommodate high shares of variable renewables.

2 Data & Methods

2.1 Modelling methodology

The overarching methodology of this paper is presented in Figure 1. The core of the approach is the long-term energy model, TIMES-Europe, with its main assumptions and input data which are equal for all model versions. An important input to this model is the solar, wind and load data, exemplified in Figure 1 with a week of hourly data for Norway and further discussed in section 2.4. This data is then aggregated or used in the scenario generation method to produce input data for the various deterministic and stochastic model versions with differing temporal resolution. Finally, the various model versions are tested and their model results and computational performance are compared. This is done to investigate their similarities, their differences, and most importantly the significance of an appropriate representation of solar and wind short-term variability in a long-term energy model of the European power sector.

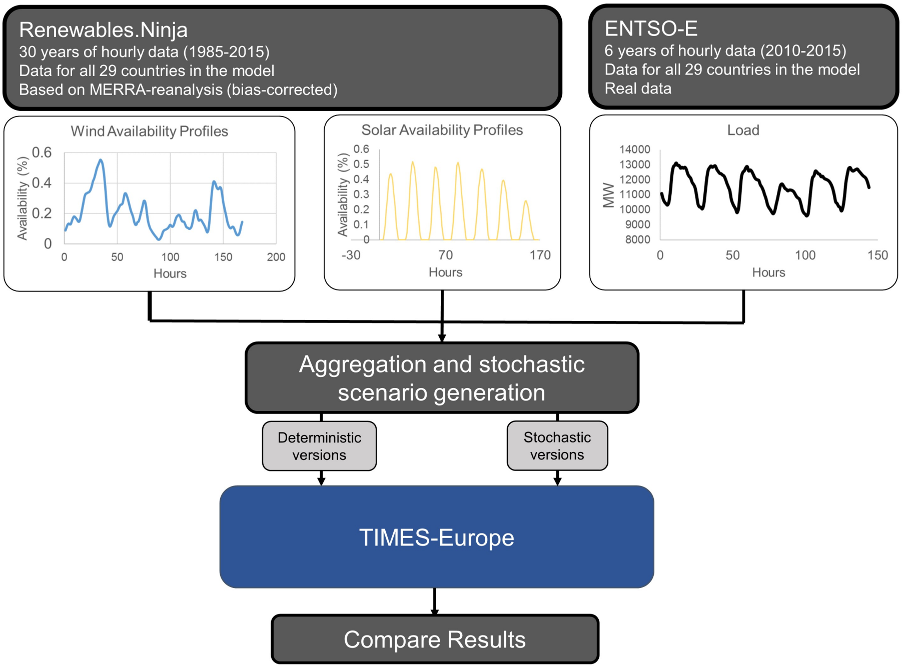

Figure 1: Overarching methodology followed in this paper

2.2 TIMES-Europe

TIMES-Europe is a least-cost optimisation model of the European power and district heat sectors developed from the well-known TIMES (The Integrated MARKAL-EFOM) modelling framework [38]. The model is based on a TIMES model of the Scandinavian energy system [32], and uses linear optimisation to treat investments in energy-infrastructure, system operation and imports of energy carriers for 29 interconnected European countries towards 2050 (see Figure 2). In order to reduce computational requirements, particularly arising from the focus on short-term variability, the model is run with investment periods of ten years. We use a discount rate of 4 %, and the currency is ^{2015}€.

A comprehensive description of the model, its assumptions and input data can be found in the model documentation in the Supplementary Materials.

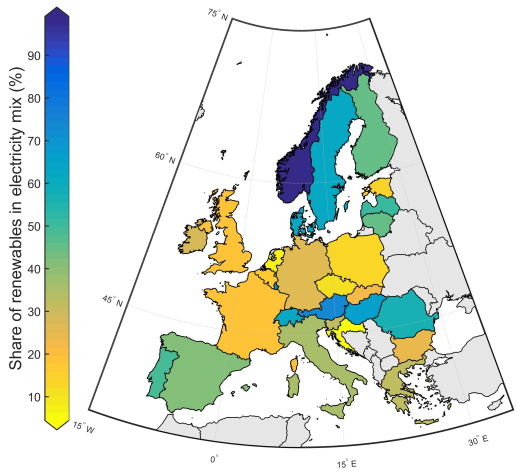

Figure 2: Modelled countries and their share of renewables in the electricity mix in 2015

2.3 Model assumptions

Despite not being the main focus of this paper, it is important that the case study of a future European power system is realistic. One of the main drivers of model results is the projection of future demand of electricity and heat. This is supplied exogenously to the model, where all national demand projections are based on the European Commission's Reference Scenario from 2016 [39]. The electricity demand increases by 27 % between 2015 and 2050 (∼3000 TWh to ∼3800 TWh), whereas the district heat demand increases by 10 % (∼610 TWh to ∼670 TWh). Many studies have shown that e.g. electrification of vehicles could lead to a steeper increase of electricity demand than what is assumed here [40–42].

National generation capacities, electricity and district heat generation as well as cross-border interconnection capacity and trade has been calibrated by statistics for the year 2015 from a number of sources (this is further elaborated in section 4 of the Supplementary Materials). This calibration is important, as the existing capacities serve as a basis for future investment needs and provides the starting point for the gradual transition to a low carbon energy system.

Import prices for coal, natural gas and oil from 2015 to 2050 are based on IEA's New Policies Scenario from the World Energy Outlook 2018 [43]. The CO_2 price in 2015 of 7.7 €/ton is based on [44], and assumed to increase to 55 €/ton in 2050 [43]. This is a conservative estimate in comparison to other similar studies. For example, Bogdanov et al. [45] assume a CO_2 price of 150 €/ton in 2050, and Zappa et al. [46] assume a CO2 price of 120 €/ton in 2050.

We have excluded all other subsidies, taxes, and national climate goals. This is a standard assumption in social planning, and is done in order to obtain the macroeconomic cost-optimal solution. The only policies included are established nuclear phase-out programs (see Supplementary Materials section 4.3.). However, the developed model tool is well suited for specific analyses of the impact of both national and Europe-wide policies.

2.4 Input data

We have used 30 years of historic nationally aggregated hourly solar and wind capacity factors (the ratio of actual energy generation during a given period to the potential generation if producing at nominal capacity during the same period), spanning from 1985 - 2015 as basis to represent short-term solar and wind variability in TIMES-Europe. Due to the significant inter-annual variability of both solar and wind, recent studies have discussed the importance of using long and coherent wind and solar data-sets in long-term energy models [27, 47].

The solar and wind data-sets are obtained from renewables.ninja, a web application based on the Global Solar Energy Estimator (GSEE) model and the Virtual Wind Farm (VWF) model [16, 48]. These models estimate hourly availability of solar and wind generation based on weather data from the MERRA reanalysis [49], and are bias-corrected for European countries using national generation data.

The wind and solar data allow us to include the effect of solar and wind correlation across Europe in our model. This could have significant implications on the wider system operation, with benefits of the smoothing effect seen when aggregating solar and wind generation over large geographical areas. It could also lead to challenges, as European-wide weather regimes could lead to longer periods of low solar and/or wind availability. Figures S4 - S7 in the Supplementary Materials show the Spearman rank correlation coefficient for solar PV, onshore wind and offshore wind generation calculated over the whole 30-year period.

The electric load data for all countries is retrieved from the European Network of Transmission System Operators (ENTSO-E), and is given on an hourly basis between 2010 and 2015 [50]. The electricity load profile is assumed to have the same shape in 2050 as it does today. This is a simplification, as it is expected that the shape of the load profile will change e.g. due to increased penetration of electric vehicles or the introduction of technologies for demand side flexibility [51]. The district heat load profile, which describes the fluctuation of district heat demand within a year, is retrieved from EnergyPlan [52, 53], and is given in hourly resolution (8760 steps per year). This is also used to create generic profiles for the model versions, and are used for all regions in TIMES-Europe. It must be noted that the inclusion of the district heat network is not the main focus of this research, but implemented to capture the cross-sector effects, which are particularly important for combined heat and power plants.

Maximum installed capacities of the various renewable energy sources as well as maximum use of biomass and waste are presented in Table S40 - 48 in the Supplementary Materials. These constraints are added in order to reflect both theoretical, environmental and social constraints to the expansion of renewable energies. As an example, the assumed maximum onshore wind capacity is based on estimates of available land area for onshore wind installations in each country, taking into account protected areas, mountainous areas etc. [54–56].

2.5 Model versions

2.5.1 Temporal resolution

In order to explore the importance of the temporal resolution and modelling methodology in long-term energy models, we have developed several model versions. Fundamentally, all versions work in the same way and with the same data, but with varying temporal resolutions. This includes versions with respectively 12, 48, 192, 672 and 2016 time slices per year (see description of time-slice division in Table 1). The number of time-slices in TIMES models usually range between 4 to 48 [29, 57], with the most detailed models having 288 time-slices [18, 29]. Our models with 672 and 2016 time-slices represent a significant increase of the temporal resolution compared to the existing literature. The different temporal resolutions are combined with two alternative ways of handling the uncertainty in the future supply.

Table 1: Temporal structure of the tested model versions

Model version	Description
12 time-steps	3 time-steps per season, consisting of a night time-slice (00.00-07.00, 7 hours), a day time-slice (07.00-23.00, 16 hours) and a peak time-slice (1 hour)
48 time-steps	12 time-steps per season, one representative day with two-hourly resolution per season
192 time-steps	48 time-steps per season, one average day with hourly resolution, and one peak day with hourly resolution that contains the peak hour of the season
672 time-steps	One week with hourly resolution per season, the week containing the peak hour of the combined European load is chosen (to keep spatial and temporal correlation)
2016 time-steps	One week with hourly resolution per month, the week containing the peak hour of the combined European load is chosen (to keep spatial and temporal correlation)

2.5.2 Deterministic approach

A conventional deterministic modelling approach considers only one operational scenario, in which the solar, wind and electricity demand profiles are based on their expected values (climatology). Consequently, the investment decisions in a deterministic model do not take into account a range of operational situations that can occur. This is the simplest approach followed in this paper.

2.5.3 Stochastic approach

We apply a two-stage stochastic model [58] to provide investment decisions in TIMES-Europe that explicitly consider various operational situations caused by the short-term uncertainty of solar PV generation, wind generation and electricity demand. Each uncertain parameter is represented by a set of 15 possible realisations, called scenarios, which all are assigned the same probability of occurrence. These scenarios are generated by a scenario generation method combining random sampling and moment matching, as described in Section 2.5.4.

Figure 3 shows a scenario tree containing the information structure of a two-stage stochastic model. The first stage involves investment decisions for the entire model horizon, from 2015 to 2050, which are made without knowing the realisation of the operational scenarios. The outcome of the operational scenarios is revealed at the second stage, where operational decisions are made for each of the scenarios and for all model periods. Investments and operational decisions are made simultaneously through applying a multi-horizon model structure [59], where no dependency of operational decisions between model periods is assumed. In order to take into account the various operational scenarios in the optimisation, the stochastic model minimises the investment costs and the average of the operational costs for all scenarios. This results in investments that take into account the expected operational cost, and are identical and feasible for all operational scenarios.

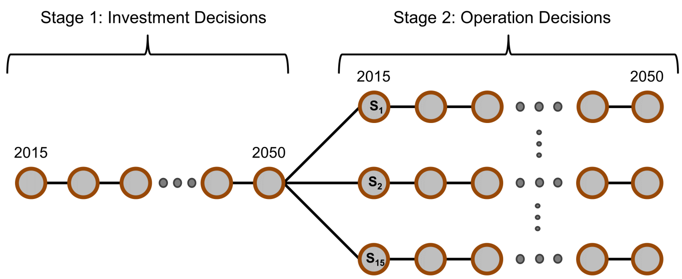

Figure 3: Illustration of a two-stage stochastic model with fifteen operational scenarios (adapted from [32])

2.5.4 Stochastic scenario generation

In the stochastic modelling approach, the generated scenarios describe the uncertainty of the solar and wind availability and in addition represent realistic operational situations [31]. Our scenarios are generated through a method that combines random sampling and moment matching [31, 35]. The technique involves:

1. Random sampling of historical days from the solar, wind and load data to construct 15 independent

scenarios (one scenario set), where each scenario follows the temporal structure of each model version. We sample consecutive hourly values, giving consistent daily correlations. Furthermore, we capture correlations between the three uncertain parameters by sampling concurrent days, and spatial correlation by sampling the same day for each region. Days are sampled separately for each season, assuming no seasonal dependency, and repeat the procedure for each investment period thus also capturing inter-annual variability.

2. Repeating this procedure 10 000 times to generate a large amount of possible scenario sets.
3. Calculating mean, variance, skewness and kurtosis (the first four moments) for the historic data and for each of the 10 000 scenario sets.
4. Calculating the deviation of the moments of each scenario set to the historical datasets, and then selecting the set of scenarios with the lowest deviation (best fit with the statistical properties of the original datasets) for use in TIMES-Europe.

2.5.5 Model versions

Table 2 presents the various model versions that have been run in this study. Some of the model versions have not been tested due to memory requirements. As the 672 and 2016 time-slice models were not solvable on a normal laptop computer[1], all model versions are run on a computer with state-of-art specifications[2]. This allows a comparison of e.g. solution time between the models, and represents computational possibilities that most likely will be the norm in the future. We also developed a model with 8760 time-slices, but were unable to solve it due to RAM limitations. This also shows why we have to reduce the temporal resolution in long-term energy-models to make them computationally tractable.

Table 2: Model runs in this study

Model version	Deterministic	Stochastic
12 time-slices	✓	✓
48 time-slices	✓	✓
192 time-slices	✓	×
672 time-slices	✓	×
2016 time-slices	✓	×

[1]Intel(R) Core(TM) i7-5600U CPU @ 2.60 GHz, 16 GB RAM
[2]Intel(R) Xeon(R) Silver 4114 CPU @ 2.20 GHz, 96 GB RAM

3 Results and discussion

In this section, we present and compare the results from the various model versions, and assess the impact of increasing the temporal resolution or modelling with a stochastic modelling approach. The stochastic model with 48 time-slices is used as a reference for comparison, in order to determine at which temporal resolution a deterministic model is able to reproduce the results. First, we investigate the energy system related results, looking at the features of a future European power system. Second, we look at the computational performance of each model version, discussing the trade-off between model accuracy and computational effort. Finally, we discuss the implications of our work and suggest topics to be explored for future studies.

3.1 Model performance

3.1.1 The European electricity mix

Figure 4 panel A and C show the European aggregated installed capacity and electricity generation in 2050. The overall composition of the system is similar across all versions, dominated by large shares of onshore wind and solar PV, but there are important differences between them.

These differences are highlighted in panel B and D of Figure 4, which show the mismatch of the installed capacity and electricity generation in 2050 for each model version relative to the stochastic model with 48 time-slices. The deterministic models with 12, 48 and 192 time-slices overestimate the contribution from solar and wind, investing in an additional 321 GW capacity of VRES in *Det12* ($\sim$17 % of total installed capacity in *Stoch48*), and about 200 GW in both *Det48* and *Det192*. Consequently, this gives 500-600 TWh (13-15% of total electricity generation) more VRES generation in 2050 in those models relative to *Stoch48*. Since the deterministic model versions treat solar and wind based on their expected generation, their availability is overestimated. The large amounts of solar and wind also leads to the 12, 48 and 192 time-slice models underestimating the need of flexibility, with significantly lower investments in flexible natural gas and biomass, as well as base-load nuclear (see Figure 4 panel B). This is also shown in panel D, which shows that the mismatched generation from solar and wind in *Det12*, *Det48* and *Det192* is largely replaced by biomass, natural gas and nuclear generation in *Stoch48*.

The *Stoch12* model also overestimates solar PV capacity, with more than 1.1 TW of solar capacity across Europe in 2050, which is 350 GW more than *Stoch48*. Furthermore, the stochastic model version works so that the fleet of technologies invested in by the model should be able to meet the energy demand in all scenarios, even those with unfavourable wind and solar conditions. In this case, due to the structure of the 12 time-slice model where the peak time-slice constitutes as much as 4 % of the year, this results in the *Stoch12* model investing in large amounts of natural gas to cover the peak hours in the stochastic scenarios with low VRES availability. This leads to a total natural gas capacity of 270 GW, which is about three times as much as in *Stoch48*.

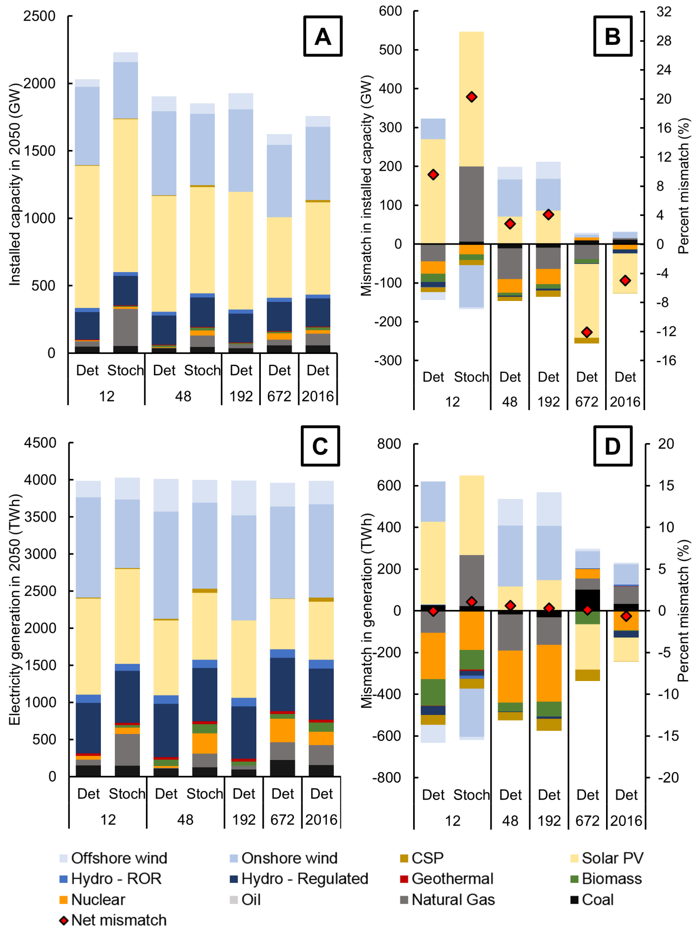

Figure 4: European aggregated installed capacity and electricity generation in 2050 and associated mismatch between model versions: Panel A shows the installed capacity in 2050, whereas panel B shows the mismatch in installed capacity relative to the *Stoch48* model. Panel C shows the electricity generation in 2050, and its associated mismatch in Panel D. The diamonds show the net mismatch, i.e. the mismatch of total installed capacity or total electricity generation, and the percent mismatch relative to the *Stoch48* model is shown on the right-axis. Also note the different y-axes in the four panels. It must be mentioned that for the stochastic model versions, the installed capacity is common for all stochastic scenarios, but the electricity generation changes for each scenario depending on VRES availability and the load curve shape. Therefore, panels C and D show the average across all stochastic scenarios. The generation in 2050 shown in panel C of about 4000 TWh is larger than the demand of 3800 TWh mentioned in the text mainly due to grid losses.

The higher temporal resolution of the *Det672* model leads to a better performance in comparison to the other deterministic models. By modelling a full week per season, this model is able to capture periods with low solar and wind availability, thus achieving results that are more similar to *Stoch48*. There is, however, a big discrepancy in the installed capacity of solar PV and natural gas. It is interesting to notice that despite the lower natural gas capacity, the actual electricity generation is higher in *Det672* in comparison to *Stoch48*. This, as was the case with *Stoch12* above, has to do with the internal structure of the stochastic model. In *Stoch48*, there are some scenarios with low VRES availability where additional natural gas generation is needed, and others with high VRES variability where natural gas is less used. This leads to a wide spread of natural gas generation across the stochastic scenarios, ranging from 82 TWh to 280 TWh. Thus, the average natural gas generation is lower in *Stoch48* than in *Det672*, but in some scenarios, which also determine the installed capacity, natural gas generation is higher.

The model performing the closest to the stochastic 48 time-sliced model is the *Det2016* model, with the only big difference being less solar PV capacity in the deterministic model. There are also some small differences in the choice of fuel in the electricity generation, but the spread of mismatched generation is reduced drastically from *Det12* to *Det2016*. The two models are also aligned in the share of renewables in the electricity mix, both with a total renewables share of 82 %, with 62 % being from variable renewables.

While Figure 4 only shows the European aggregated results for 2050, figures S20 - S33 in the Supplementary Materials show the development in installed capacity and electricity generation from 2015 to 2050 for each country for all model versions. These figures strengthen the impression that *Det672* and *Det2016* perform well in reproducing the results from *Stoch48*.

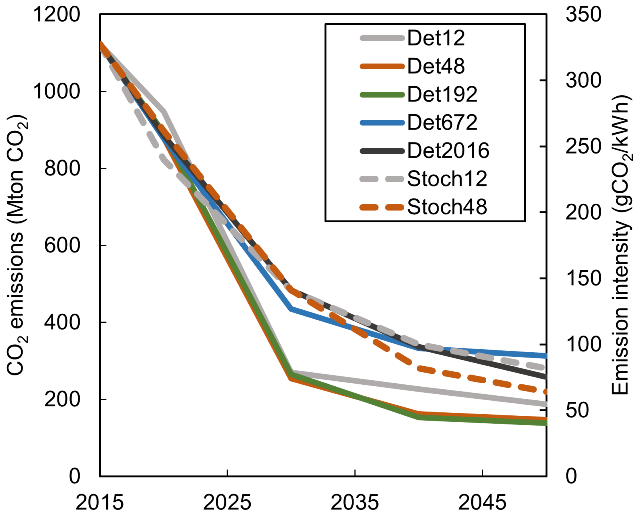

Figure 5: Estimated CO_2 emissions from 2015 to 2050

The transition to a power system based primarily on renewable energy sources also leads to major cuts in CO_2 emissions. The emission cuts range from 72 % to 88 % in the various model versions, with the low-resolution deterministic model generally achieving the highest emission reductions. High emission reductions are also obtained in *Stoch48*, but this depends strongly on the given stochastic scenario, with emissions ranging from 190 Mton CO_2 to 290 Mton CO_2.

Figure S35 in the supplementary materials shows the district heat generation in 2050 for each model version. By the middle of the century, there is still a large contribution (about 40 % in *Stoch48*) from fossil-fuel powered combined heat and power plants and natural gas boilers for district heating. The remainder of the demand is mostly served by electrified heating (mostly heat pumps), biomass as well as solar thermal heating.

3.1.2 Flexibility requirements

In a future Europe with high shares of variable renewables, there is a significant need for flexibility to match the variable renewable generation. As already discussed, the low resolution deterministic model versions (12, 48 and 192 time-slices) put too much trust in renewables to generate electricity when needed, systematically underestimating the need for flexible and base-load generation (Figure 6 panel A). In addition to flexible generation, additional sources of flexibility can help the integration of large shares of variable renewables. Significant investments in the European transmission grid is seen in all model versions (Figure 6 panel B), with more than a doubling of total interconnection capacity. Energy storage will also be an important source of flexibility. Figure 6 panel C shows the new energy storage capacity in the various model versions. Pumped hydro storage (PHS) utilises all its available potential in almost all model versions, and lithium-ion batteries are also very popular. Hydrogen storage sees a very limited role in the future power sector, but this could change if the present model is expanded to also include the transport sector.

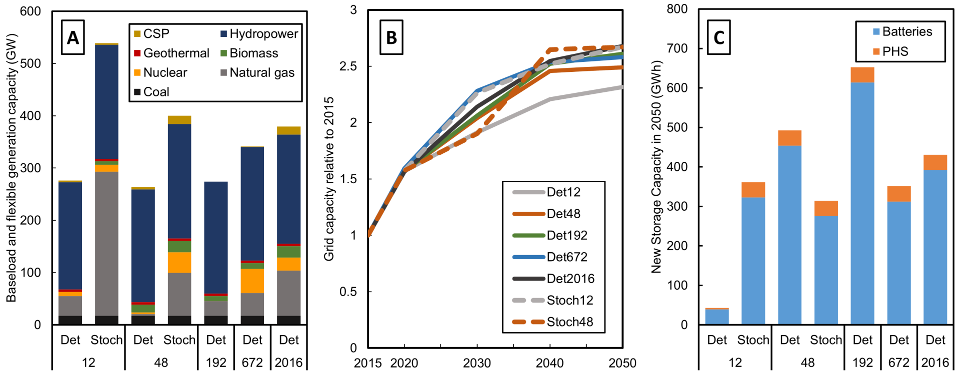

Figure 6: Sources of flexibility: A) shows the installed capacity of baseload and flexible generation in 2050, B) shows the development of the transmission grid relative to 2015, and C) shows new storage capacity in 2050 (i.e. not existing installed PHS capacity)

The previous sections have shown that both *Det672* and *Det2016* achieve similar results as *Stoch48*. By applying a test called the Value of Stochastic Solution (VSS), we can expose the resulting energy system configuration from *Det672* and *Det2016* to the same short-term uncertainty as modelled in *Stoch48*. This will provide a measure of the value of following a stochastic approach relative to a deterministic one [31, 60]. The VSS works by fixing the investments from a deterministic model and then running the model with the stochastic operational scenarios. In other words, we take the investments from *Det672* and *Det2016*, implement them in *Stoch48*, and then run them with the fifteen operational scenarios without allowing new investments. For both *Det672* and *Det2016*, the VSS leads to infeasible solutions. The deterministic investment strategy leads to a system that is not able to meet the demand in 14 out of 15 scenarios for *Det672* in 2050, and in 7 scenarios for *Det2016*. This shows that the deterministic models underestimate the need for flexibility in comparison to the stochastic model.

A common way of ensuring enough back-up capacity in deterministic models is to use a heuristic that limits the contribution from VRES and ensures investment in flexible generation capacity [32]. We have tested running our deterministic models with operational peaking constraints, with the approach and results presented in the supplementary materials. For the low temporal resolution models, adding this constraint did not have significant impact on the results. The results are very similar to the other deterministic models, with the exception that the peaking reserve constraint leads to more investments in natural gas capacity, including open cycle gas turbines (OCGT). This is the cheapest capacity available, and is only invested in to satisfy the peaking reserve constraint, but rarely used.

It does, however, make an impact for the deterministic models with higher resolution. The additional flexible capacity in these models, leads to a feasible solution when tested for the VSS, which without the peaking reserve constraint led to infeasible solutions. The relative VSS is found to be 6% for *Det672*, indicating that the total system cost is higher for the deterministic model solution when uncertainty is present. This is mainly due to the extra investments in OCGT capacity and the expensive use of this capacity in periods with low solar and wind availability. This highlights the caveat of the peaking reserve approach, as the reserve requirements are set exogenously and are not a result of endogenous model decisions. Due to memory requirements, *Det2016* proved impossible to run with additional peaking constraints on the current computer setup. However, similar results as shown with *Det672* are to be expected.

3.1.3 Costs of a highly renewable European power system

Figure 7 shows the aggregated annual costs for the European power and district heat systems in 2050, divided into investment costs, fuel costs, O&M costs and CO_2 taxes. The annual costs range from ∼150b€/year to ∼200b€/year depending on the model version. Due to their overestimation of the contribution from variable renewables, *Det12*, *Det48* and *Det192* underestimate the expenditures in all cost segments. This leads to large underestimations of total annual costs, being 30-35 b€/yr (15-20%) lower than *Stoch48*. On the other hand, *Stoch12* overestimates the fuel and CO_2 costs, mainly due to high natural gas usage, which in turn gives annual costs about 10 b€/yr (5 %) higher than *Stoch48*.

The closest results are achieved for *Det2016* and *Det672*, with annual costs that deviate by respectively 1.5 and 5 billion euros per year in comparison to *Stoch48* (0.8 and 2.6 % deviation). These minor deviations occur due to slightly higher investment and O&M costs in *Stoch48*, which are compensated by higher fuel and CO_2 costs in *Det672* and *Det2016*. This is also an indication that *Stoch48* invests more in a system capable to serve the demand in all stochastic scenarios, but this additional capacity might only be used in a couple of the scenarios. In fact, the total annual costs in *Stoch48* range from 185-200 b€/yr across the scenarios, depending on VRES availability and the need to use fossil fuels (investments costs and O&M costs are of course equal in all scenarios). On the other hand, the deterministic models only optimise on the basis of one scenario, where it is cheaper to invest in less capacity but with a higher utilisation. However, it is this investment strategy that leads to challenges when exposed to the variability of the operational scenarios in the VSS tested above (section 3.1.2).

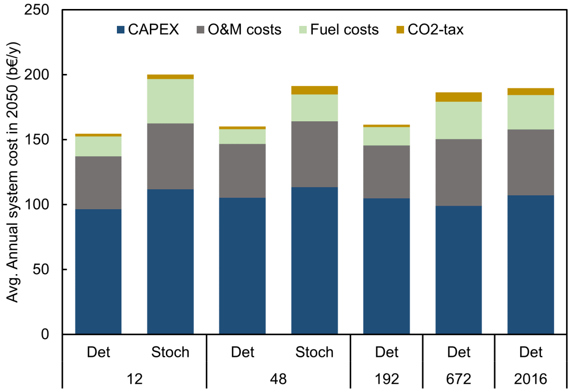

Figure 7: Average annual system costs in 2050

The maps in figure 8 show the electricity shadow price in 2050 for each country in A) *Det48*, B) *Det672*, C) *Det2016*, and D) *Stoch48*. All these model versions are able to capture the spatial trends across Europe, even the simple low resolution *Det48* model. The outskirts of Europe generally achieve lower prices, whereas the big load centres in the middle of Europe (e.g. France, Germany and Italy), have higher prices. This trend occurs due to the north and south of Europe having the best resource potential for renewable energy sources (high wind potential in the north and high solar potential in the south). A lot of renewable capacity is therefore built in these regions, with additional investments in grid interconnections to transfer the electricity to central Europe. The surplus of electricity thus leads to low prices in these regions, while the import dependency of the central European countries gives higher prices. This is particularly the case in time-slices with low availability of renewables, which leads to less cheap electricity being available for import, thus increasing the need for more expensive fossil fuel use pressing prices upwards.

All deterministic models in Figure 8 return lower shadow prices than *Stoch48*. While *Stoch48* estimates the average European shadow price to be ~61.2 €/MWh, the prices in *Det48*, *Det672* and *Det2016* range between 57.7 to 58.7 €/MWh, corresponding to a deviation of 4-6%.

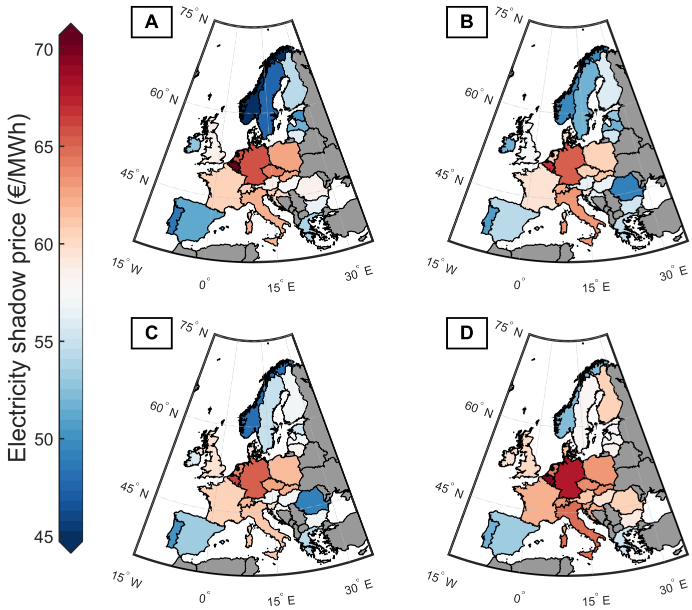

Figure 8: Average electricity shadow prices by country in 2050 for A) *Det48*, B) *Det672*, C) *Det2016*, and D) *Stoch48*

3.1.4 Stability

This paper uses 15 stochastic scenarios to represent the short-term variability of solar and wind generation as well as electricity demand. It is often desirable to reduce the number of scenarios in a stochastic model due to computational requirements, but this could give model results that depend on the scenarios rather than the underlying data [61]. We test the in-sample stability on the stochastic model with 48 time-slices to evaluate whether the number of scenarios used in this paper is sufficient to have a stable solution. Testing in-sample stability involves testing if solving the stochastic model gives approximately the same objective function value when using different scenario trees based on the same underlying data and scenario generation method (2.5.4). This also includes assessing whether the value of the objective function is stable when increasing the number of scenarios. However, increasing the number of scenarios is challenging, as it quickly leads to high computational requirements. We have run 20 model instances, involving 5 runs for each of 3, 9, 15 and 30 scenarios respectively, with the results shown in Supplementary Figure S34. The value of the objective function is generally stable from 9 to 30 scenarios. Consequently, we assume that 15 scenarios are satisfactory for the purpose of this paper.

3.2 Computational performance

An important discussion point is the trade-off between accuracy and computational effort in the model versions. While stochastic models have been shown to give a more realistic representation of short-term solar and wind variability in models with low temporal resolution, they are complicated, need intricate preprocessing and have long run times relative to deterministic models with the same resolution (see Figure 9 and Table 3). The deterministic model version with 48 time-slices takes less than a minute to solve, whereas the same model with a stochastic approach takes more than ten hours.

As the previous sections have shown, only the deterministic model versions with 672 and 2016 time-slices come close to reproduce the results from *Stoch48*. However, *Det672* has a solution time almost equal to *Stoch48*, whereas *Det2016* is almost 30 times longer. Given that both fail the VSS, this suggests that the stochastic modelling approach is able to weigh up for its lower temporal resolution.

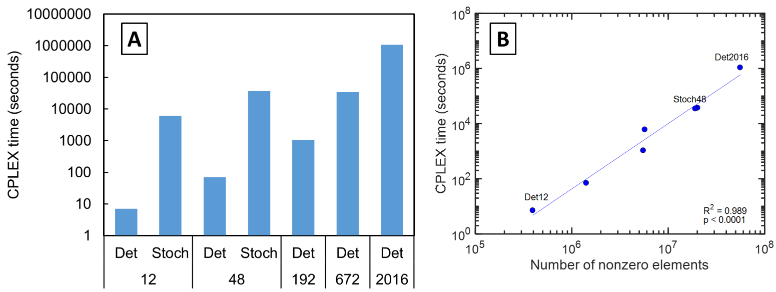

Figure 9: CPLEX time in seconds for A) each model version and B) relative to number of nonzero elements (note the logarithmic axes)

Table 3: Computational performance of tested model versions (nonzero elements, equations and variables are reported after aggregation)

Model version	**Time (s)**	**Time (h)**	**Nonzero elements**	**Equations**	**Variables**
Det12	7.1	~0	393623	69319	80778
Stoch12	6078	~2	5717225	1037871	1078179
Det48	69.9	~0	1413852	230953	275513
Stoch48	37141	~10	20183347	3237170	3679885
Det192	1060	~0.3	5507870	879168	1053827
Det672	34606	~10	19079446	3022448	3631491
Det2016	1075263	~299	55805140	8821290	10633679

3.3 Outlook

This paper has investigated the importance of an adequate representation of short-term solar and wind variability in long-term energy models. We have compared a conventional deterministic approach to a stochastic approach, and have also assessed the effect of increasing the temporal resolution. In addition, we have discussed the introduction of a heuristic that limits the contribution of VRES, and how it can improve the output from deterministic models. We have not, however, compared the stochastic modelling approach to more sophisticated methods of selecting time-slices. Both *Det672* and *Det2016* are based on heuristic methods, selecting a week of hourly data based on the occurrence of the combined European peak hour in that week. Other methods could also be tested, using e.g. clustering algorithms or optimisation techniques to better select the time-slices. This could improve the performance of the deterministic models, potentially to the extent that it could replicate the results achieved with the stochastic model version. However, such techniques would also add to the complexity and intricate pre-processing, which is a drawback of the stochastic model version used in this paper. Another approach that could be further investigated is the coupling of long-term energy models to operational power systems models. This could reduce the temporal resolution needed in the long-term energy model, while simultaneously capturing the detailed operation of the system.

While this paper focuses on the temporal aspects of wind and solar integration, the spatial resolution is limited to country level. This simplification undermines how generation and demand is distributed within each country and the bottlenecks that could occur. An example is the German power grid, where bottlenecks between the windy north and the industrial south leads to congestion and overloading [62]. Our assessment on a national scale could therefore underestimate necessary investment in the distribution grid, even though our costs for cross-country transmission lines are overestimated to also take into account improvements in the distribution grid. A better spatial representation could give important information about the placement of new renewable capacity, to minimise land-use impacts and to avoid social conflicts [63]. Since TIMES has been heavily used in national and sub-national studies, the present establishment of a European version enables comparison, exchange of parameters and perhaps even coupling of models on different scales. It is then important to remember that the present model optimises the power and district heating systems of a collective Europe, and not each individual country.

The demand side of the energy system could be another source of flexibility to ease the integration of VRES. In addition to energy efficiency measures, demand response (DR) could actively help matching the demand to the available supply through shifting load in time, change load profiles or even curtail load [37]. Additional sector coupling, not only with the district heat sector as in this paper, but also with e.g. the transport sector could improve flexibility through intelligent EV charging or even using EV batteries as a means of storage [64].

Finally, our results lead to a VRES share of about 60 % of the electricity generation, with a total renewable share of about 85 %. In order to meet the 1.5 degree target, the IPCC state that the emissions must be halved by 2030 and reach net-zero by 2050 [65]. As other sectors such as transportation and industry are harder to decarbonise, the power sector is seen as key for cutting emissions. Therefore deeper emission reductions in the power sector than what is achieved here would be required. Additional scenarios that require 100 % renewable energy or zero CO_2 emissions would be interesting to assess, in order to increase the VRES share and investigate how this affects the flexibility requirements of the European power system.

4 Conclusions

The future European power system is expected to contain large shares of variable electricity generation, particularly from solar and wind technologies. Long-term energy system models are often used to provide insights of power market transitions with large shares of renewables, and require therefore an appropriate representation of short-term solar and wind variability. In this work, we have assessed the representation of solar and wind variability in a TIMES long-term energy model of the European power and district heat sectors towards 2050.

We have shown that an accurate representation of short-term solar and wind variability is highly important when modelling the future European power system. When compared to a stochastic model with 48 time-slices, deterministic models with a too coarse temporal resolution underestimate annual costs in the range of 15-20% and overestimate the contribution from variable energy sources from 13 to 15% of total electricity generation. Consequently, this leads to an underestimation of CO_2 emissions and the required flexibility to handle solar and wind variability.

A better approximation of the results from the stochastic 48 time-slice model is only achieved when significantly increasing the temporal resolution to 672 or 2016 time-slices. The 2016 time-slice model achieves the closest results to the stochastic 48 time-slice model, with a generation mismatch of about 5 %, and a deviation of annual system costs of 0.8 %. However, both the 672 and 2016 time-sliced models invest in too little flexibility to handle the same short-term uncertainty as the stochastic model, needing an added peaking constraint to achieve feasible results. In addition, while the deterministic model with 672 time-slices takes as much time to run as the stochastic one, the 2016 time-slice model is 30 times slower. This shows that a stochastic model version with 48 time-slices is able to weigh up for a low temporal resolution in comparison to very high temporal resolution deterministic models, both in terms of solution time and model accuracy.

The choice of temporal resolution and modelling approach plays thus an important role both in model results and insights as well as computational performance of long-term energy models, and should be carefully evaluated when such models are used for decision-making. When modelling an energy system consisting of large shares of variable renewable energy sources, a stochastic modelling approach that takes into account the uncertainty of their short-term variability is recommended, both due to its accuracy and also its computational efficiency in comparison to high-resolution deterministic models.

Our case-study has also shown that a large share of renewable electricity generation is the most-preferred pathway for the European power and district heat systems. This is achieved with a conservative CO_2 tax, and without emission constraints or targets for renewables share. This shows that new renewables already are, and to an increasing extent will be, competitive with fossil fuelled power generation. Future studies could use a stochastic long-term energy systems model to investigate such aspects and assess even more radical transformations, considering e.g. 100 % renewable energy or zero emission scenarios. Further studies should also assess other time-slice selection techniques to improve the deterministic model versions.

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Appendix A

Supplementary material to Paper II

Supplementary material

Transitioning remote arctic settlements to renewable energy systems – a modelling study of Longyearbyen, Svalbard

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Table S1 – Technological parameters and costs

Solar PV (Ground - South)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	25	25	25	25	25	25	25	25	[1,2]
Capacity Factor (%)	7.67	7.67	7.67	7.67	7.67	7.67	7.67	7.67	-
Investment Cost (kNOK/MW)	13338	11604	9870	8136	6402	6402	6402	6402	[1,2]
O&M Cost (kNOK/MW/year)	134	117	100	83	66	66	66	66	[1,2]
Solar PV (Residential - Northwest)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	25	25	25	25	25	25	25	25	[1,2]
Capacity Factor (%)	6.03	6.03	6.03	6.03	6.03	6.03	6.03	6.03	-
Investment Cost (kNOK/MW)	16975	14768	12562	10355	8148	8148	8148	8148	[1,2]
O&M Cost (kNOK/MW/year)	85	74	63	52	41	41	41	41	[1,2]
Solar PV (Residential - Southeast)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	25	25	25	25	25	25	25	25	[1,2]
Capacity Factor (%)	7.22	7.22	7.22	7.22	7.22	7.22	7.22	7.22	-
Investment Cost (kNOK/MW)	16975	14768	12562	10355	8148	8148	8148	8148	[1,2]
O&M Cost (kNOK/MW/year)	85	74	63	52	41	41	41	41	[1,2]
Onshore Wind	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	20	20	20	20	20	20	20	20	[1,2]
Capacity Factor (%)	26.3	26.3	26.3	26.3	26.3	26.3	26.3	26.3	-
Investment Cost (kNOK/MW)	12640	11882	11123	10365	9606	9606	9606	9606	[1,2]
Variable O&M Cost (kNOK/MW/year)	116	109	102	95	88	88	88	88	[1,2]
Offshore Wind (Monopile)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	20	20	20	20	20	20	20	20	[1,2]
Capacity Factor (%)	31.9	31.9	31.9	31.9	31.9	31.9	31.9	31.9	-
Investment Cost (kNOK/MW)	45546	43724	41903	40081	38259	38259	38259	38259	[1,2]
O&M Cost (kNOK/MW/year)	970	931	893	854	815	815	815	815	[1,2]
Offshore Wind (Floating)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	20	20	20	20	20	20	20	20	[1,2]
Capacity Factor (%)	31.9	31.9	31.9	31.9	31.9	31.9	31.9	31.9	-
Investment Cost (kNOK/MW)	54252	52082	49912	47741	45571	45571	45571	45571	[1,2]
O&M Cost (kNOK/MW/year)	1500	1440	1380	1320	1260	1260	1260	1260	[1,2]
Hydrogen Electrolyser (Alkaline)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**

Lifetime (years)	10	10	10	10	10	10	10	10	[3]
Efficiency (%)	0.63	0.64	0.65	0.66	0.67	0.68	0.69	0.70	[3]
Availability Factor (%)	98	98	98	98	98	98	98	98	[3]
Investment Cost (kNOK/MW)	16 653	11 281	10 923	10 385	9 848	9 848	9 848	9 848	[3]
O&M Cost (kNOK/MW/year)	304	282	260	237	237	237	237	237	[3]
Hydrogen Electrolyser (PEM)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (Years)	8	9	9	9	9	9	9	9	[3]
Efficiency (%)	0.63	0.68	0.69	0.71	0.71	0.71	0.71	0.71	[3]
Availability Factor (%)	97	98	98	98	98	98	98	98	[3]
Investment Cost (kNOK/MW)	28 112	17 906	15 578	11 997	11 997	11 997	11 997	11 997	[3]
O&M Cost (kNOK/MW/year)	439	379	319	260	260	260	260	260	[3]
Hydrogen Fuel Cell (PEMFC)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	7	8	8	9	9	9	9	9	[4,5]
Electrical Efficiency (%)	35	40	43	45	45	45	45	45	[4,5]
Availability Factor (%)	97	97	97	97	97	97	97	97	[4,5]
Heat to power ratio (-)	1.6	1.25	1.11	1.0	1.0	1.0	1.0	1.0	[4,5]
Investment Cost (kNOK/MW)	26 947	20 294	13 642	6 989	6 989	6 989	6 989	6 989	[4,5]
O&M Cost (kNOK/MW/year)	1 347	1 015	682	349	349	349	349	349	[4,5]
Liquid Hydrogen Storage	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	20	20	20	20	20	20	20	20	[6]
Storage Efficiency (%)	70	70	70	70	70	70	70	70	[7]
Boil-off rate (%/year)	40	40	40	40	40	40	40	40	[8]
Investment Cost (kNOK/GWh)	140 011	92 116	74 984	56 655	42 807	42 807	42 807	42 807	[6]
O&M Cost (kNOK/GWh/year)	3 500	2 303	1 874	1 416	1 070	1 070	1 070	1 070	[6]
Battery Storage (Li-ion)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	10	10	10	10	10	10	10	10	[9]
Charge Efficiency (%)	100	100	100	100	100	100	100	100	[9]
Storage Efficiency (%)	90	90	90	90	90	90	90	90	[9]
Discharge Efficiency (%)	100	100	100	100	100	100	100	100	[9]
Investment Cost (Charge) (kNOK/MW)	1 612	1 275	1 009	799	632	500	396	313	[9]
Investment Cost (Storage) (NOK/kWh)	3 581	3 134	2 706	2 352	2 045	2 045	2 045	2 045	[9]
Investment Cost (Discharge) (kNOK/MW)	1 612	1 275	1 009	799	632	500	396	313	[9]
O&M Cost (kNOK/GWh/year)	50 137	43 582	37 884	32 931	28 625	28 625	28 625	28 625	[9]
Variable Costs (Storage) (kNOK/GWh)	23	23	23	23	23	23	23	23	[9]

Heat Pump (Geothermal)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	20	20	20	20	20	20	20	20	[1,2]
Coefficient of Performance (COP) (-)	3.60	3.96	4.32	4.68	4.68	4.68	4.68	4.68	[1,2]
Investment Cost (kNOK/MW)	13423	12752	12081	11409	10738	10738	10738	10738	[1,2]
Variable Cost (kNOK/GWh)	12	12	12	12	12	12	12	12	[1,2]
O&M Cost (kNOK/MW/year)	23	23	23	23	23	23	23	23	[1,2]
Heat Pump (Sea Water)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	15	15	15	15	15	15	15	15	[1,2]
Coefficient of Performance (COP) (-)	2.90	3.19	3.48	3.77	3.77	3.77	3.77	3.77	[1,2]
Investment Cost (kNOK/MW)	6816	6475	6135	5794	5453	5453	5453	5453	[1,2]
Variable Cost (kNOK/GWh)	12	12	12	12	12	12	12	12	[1,2]
O&M Cost (kNOK/MW/year)	29	28	26	25	23	23	23	23	[1,2]
Electric Boiler (District Heating)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	20	20	20	20	20	20	20	20	[1,2]
Efficiency (%)	98	98	98	98	98	98	98	98	[1,2]
Investment Cost (kNOK/MW)	766	766	766	766	766	766	766	766	[1,2]
O&M Cost (kNOK/MW/year)	4	4	4	4	4	4	4	4	[1,2]
Solar heating (Ground mounted)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	25	25	25	25	25	25	25	25	[1,2]
Capacity Factor (%)	8.98	8.98	8.98	8.98	8.98	8.98	8.98	8.98	-
Investment Cost (kNOK/MW)	5543	4822	4102	3381	2660	2660	2660	2660	[1,2]
O&M Cost (kNOK/MW/year)	28	25	21	18	14	14	14	14	[1,2]
Solar heating (Residential - Northwest)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	25	25	25	25	25	25	25	25	[1,2]
Capacity Factor (%)	7.18	7.18	7.18	7.18	7.18	7.18	7.18	7.18	-
Investment Cost (kNOK/MW)	8315	7234	6153	5072	3991	3991	3991	3991	[1,2]
O&M Cost (kNOK/MW/year)	42	37	31	26	20	20	20	20	[1,2]
Solar heating (Residential - Southeast)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**Ref**
Lifetime (years)	25	25	25	25	25	25	25	25	[1,2]
Capacity Factor (%)	8.57	8.57	8.57	8.57	8.57	8.57	8.57	8.57	-
Investment Cost (kNOK/MW)	8315	7234	6153	5072	3991	3991	3991	3991	[1,2]
O&M Cost (kNOK/MW/year)	42	37	31	26	20	20	20	20	[1,2]

UTES	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Lifetime (years)	20	20	20	20	20	20	20	20	[6]
Storage Efficiency (%)	70	70	70	70	70	70	70	70	[6]
Investment Cost	82 575	82 575	82 575	82 575	82 575	82 575	82 575	82 575	[6]
O&M Cost (kNOK/GWh/year)	1 650	1 650	1 650	1 650	1 650	1 650	1 650	1 650	[6]

Diesel Generators	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Lifetime (years)	25	25	25	25	25	25	25	25	[1,2]
Efficiency (%)	41	41	41	41	41	41	38	38	[1,2]
Availability Factor (%)	97	97	97	97	97	97	97	97	[1,2]
Investment Cost (kNOK/MW)	4218.5	4218.5	4218.5	4218.5	4218.5	4218.5	4218.5	4218.5	[1,2]
O&M Cost (kNOK/MW/year)	462.7	462.7	462.7	462.7	462.7	462.7	462.7	462.7	[1,2]
Variable Costs (ex. Fuel) (kNOK/MWh)	4.8	4.8	4.8	4.8	4.8	4.8	4.8	4.8	[1,2]
Fuel Cost (NOK/MWh)	974	974	974	974	974	974	974	974	[1]
Emissions (kgCO2/kWh)	240	240	240	240	240	240	240	240	[1,2]

Gas Turbines	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Lifetime (years)	25	25	25	25	25	25	25	25	[1,2]
Efficiency (%)	36	36	36	36	36	36	36	36	[1,2]
Availability Factor (%)	87	87	87	87	87	87	87	87	[1,2]
Investment Cost (kNOK/MW)	5 922	5 774	5 626	5 478	5 330	5 330	5 330	5 330	[1,2]
O&M Cost (kNOK/MW/year)	283	276	269	262	254.9	254.9	254.9	254.90	[1,2]
Variable Costs (ex. Fuel) (kNOK/MWh)	94.1	91.8	89.4	87.1	84.7	84.7	84.7	84.7	[1,2]
Fuel Cost (NOK/MWh)	249	249	249	249	249	249	249	249	[1,2]
Emissions (kgCO2/kWh)	200	200	200	200	200	200	200	200	[1,2]

Gas Turbine - CHP	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Lifetime (years)	20	20	20	20	20	20	20	20	[1,2]
Efficiency (%)	33	33	33	33	33	33	33	33	[1,2]
Power to heat ratio (-)	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	[1,2]
Coefficient of electricity to heat (CEH)	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	[1,2]
Availability Factor (%)	68.5	68.5	68.5	68.5	68.5	68.5	68.5	68.5	[1,2]
Investment Cost (kNOK/MW)	11 002	10 864	10 727	10 589	10 452	10 452	10 452	10 452	[1,2]
O&M Cost (kNOK/MW/year)	314	310	306	303	299	299	299	299	[1,2]
Variable Costs (ex. Fuel) (kNOK/MWh)	66.9	66.1	65.3	64.4	63.6	63.6	63.6	63.6	[1,2]
Fuel Cost (NOK/MWh)	249	249	249	249	249	249	249	249	[1,2]
Emissions (kgCO2/kWh)	200	200	200	200	200	200	200	200	[1,2]

[1] Personal communication with Longyearbyen Lokalstyre

Table S2. Energy efficiency measures

Four energy efficiency measures in buildings are included, and are based on [10,11]. Their lifetime, energy savings potential and costs are shown in Table S2. **Energy monitoring**: installing an energy monitoring system, which shows the consumption for technical equipment, lighting, ventilation, heating etc. in the building. It also includes installing individual heat measurement and instructions for operation and maintenance. **Insulation and tightening:** insulation of walls, ceilings, floors and tightening of windows and air sealing (this measure reduces heat demand only). **Technical equipment (Best available technology - BAT):** heating systems, solar shading, building management systems, water treatment plans, low energy luminaires and heat recovery in ventilation systems. **Energy management:** Automatic control of lighting, heat and ventilation based on need.

	Lifetime (years)	Potential	Inv. cost (NOK/kWh)
Energy monitoring			
Existing dwellings	10	1.6 %	1.9
New dwellings	10	1.8 %	1.5
Commercial and public buildings	10	1 %	2
Insulation and tightening			
Existing dwellings	30	7.7 %	16.2
New dwellings	30	10.0 %	11.2
Commercial and public buildings	30	3.1 %	19
Technical equipment (BAT)			
Existing dwellings	15	2.8 %	12.5
New dwellings	15	3.0 %	15
Commercial and public buildings	15	1.3 %	23
Energy management			
Existing dwellings	10	2.2 %	8.8
New dwellings	10	3.6 %	20
Commercial and public buildings	10	1.7 %	13

Text S3. Technical Potential of Solar Thermal Collectors

Due to their better efficiency, ability to deliver higher temperatures and lower thermal losses, evacuated tube collectors are likely to perform better than flat plate collectors in Arctic climate, and are therefore considered in this estimate. An evacuated tube collector consists of an absorber enclosed by a glass tube with vacuum in between. Due to virtually no heat transfer occurring in the vacuum, the evacuated collector has very favourable insulation capacities. This also means that the collector works well when there is a large difference between the ambient temperature and the collector temperature.

The heat generation from a solar thermal collector can be expressed by [12]:

$$P_C = A_c\eta_0\left(G_{dir}K_\theta + G_{diff}K_{\theta=60}\right) - a_1 * (T_c - T_a) - a_2 * (T_c - T_a)^2$$

where:

P_C = Heat generation from solar thermal collector (W)
A_c = Area of collector (m^2)
η_0 = Collector efficiency (-)
G_{dir} = Direct normal irradiance (W/m^2)
G_{diff} = Diffuse irradiance (W/m^2)
K_θ = Incidence angle modifier (IAM) for the angle of incidence at the given time step (-)
$K_{\theta=60}$ = IAM for diffuse irradiance (-)
a_1 = First order heat loss coefficient (W/Km^2)
a_2 = Second order heat loss coefficient (W/K^2m^2)
T_c = Collector temperature (°C)
T_a = Ambient temperature (°C)

This equation takes into account the heat loss from the collector, the individual contributions from direct and diffuse irradiance as well as the effect of a varying angle of incidence on the performance of the collector.

We have retrieved collector parameters (η_0, a_1, a_2, K_θ and $K_{\theta=60}$) from test results on a commercially available collector [13]. The efficiency is found to be 0.734, the first order heat loss coefficient is 1.529 W/m^2K and the second order heat loss coefficient is 0.0166 W/m^2K. The incidence angle modifier (IAM) is given in table S2.

The data for solar power generation from renewables.ninja also contained raw time-series data of direct normal irradiance, diffuse irradiance and ambient temperature. We have modified these time-series into climatological daily profiles for each season, enabling us to calculate daily profiles of solar thermal generation that fits with the representative time-slice resolution used in TIMES-Longyearbyen. Since we use the same data as for the PV panels, we also assume that the solar thermal collectors can be installed in the same locations. This means that we have a ground-mounted solar collector facing south with a tilt of 30°, and two residential collectors facing northwest and southeast, both with a tilt of 20°. Installation of residential solar thermal collectors will of course restrict the available area for residential PV panels, and is taken into account in the model.

The incidence angle modifier (IAM) is used to correct a solar collector's efficiency when the irradiance comes from angles that are not perpendicular to the collector. Typically, flat plate collectors achieve their maximum efficiency at normal irradiance, and the performance is reduced when the incidence angle increases. However, for evacuated tubes the maximum efficiency might not occur at the normal incidence angle. Due to the cylindrical shape of the vacuum tubes, the reflection from neighbouring tubes can increase at higher incidence angles and can lead to IAM factors above one.

The IAM factor is given by the ratio of the collector efficiency at a given angle of incidence relative to the collector efficiency at normal irradiance:

$$K_\theta(\theta_l, \theta_t) = \frac{\eta_0(\theta)}{\eta_0}$$

The incidence angle modifier for an evacuated tube solar collector is specified for both the transversal and longitudinal incidence angles, θ_l and θ_t (see [14] for illustration), where the overall IAM factor is the product of the two:

$$K_\theta(\theta_l, \theta_t) = K_\theta(\theta_l, 0) * K_\theta(0, \theta_t)$$

The values of $K_\theta(\theta_l, 0)$ and $K_\theta(0, \theta_t)$ are found by linear interpolation in table NN. For diffuse irradiance, which comes from all angles between 0 and 90, an average value of K_θ at 60 ° is used [12].

Table S2: Test results for the Incidence Angle Modifier (IAM)

θ	0	±10	±20	±30	±40	±50	±53	±60	±70	±80	±90
$\boldsymbol{K_\theta(\theta_t)}$	1.00	1.00	1.03	1.11	1.25	1.37	1.40	1.36	1.11	0.70	0.05
$\boldsymbol{K_\theta(\theta_l)}$	1.00	1.00	1.00	0.99	0.96	0.92	0.88	0.84	0.69	0.44	0.00

The incidence, longitudinal and transversal angles are found by the following equations [15]:

$$\theta = \arccos\left(\cos(\theta_s) * \cos(\beta) + \sin(\theta_s) * \sin(\beta) * \cos(\phi_s - \gamma)\right)$$

$$\theta_l = \arctan\left(\frac{\sin(\theta_s) * \sin(\phi_s - \gamma)}{\cos(\theta)}\right)$$

$$\theta_t = -\arctan(\tan(\theta_s) * \cos(\phi_s - \gamma)) - \beta$$

where:

$\theta =$ Incidence angle
$\theta_s =$ Solar zenith angle
$\theta_l =$ Longitudinal incidence angle
$\theta_t =$ Transversal incidence angle
$\beta =$ Collector tilt angle
$\phi_s =$ Azimuth angle
$\gamma =$ Collector orientation

The zenith angle, θ_s, is the angle between the sun and the vertical, whereas the azimuth angle, ϕ_s, is the angle of the sun's position on the horizontal plane. These angles are found by calculating the sun's position for every hour through the representative days for each of the four seasons. For simplicity, we have chosen the day in the middle of each season: April 15th (day number 105) for spring, July 16th (197) for summer, October 16th (289) for autumn and Jan 14th (14) for winter. A number of calculations are needed to calculate the solar zenith and azimuth angle, summarized in table S3 below:

Table S3: Equations for calculating the sun's position on the sky

Parameter	Equation	Description
Declination Angle	$\delta = 23.45° * \sin\left[\frac{360(284+n)}{365}\right]$	Angle between the equator and a straight line from the centre of the earth to the centre of the sun, n is the number of a day in the year
Local standard time meridian	$LSTM = 15° * \Delta T_{GMT}$	Reference meridian for a particular time zone, ΔT_{GMT} is the difference of the local time (LT) from Greenwich Mean Time (GMT)
Equation of time	$EoT = 9.87\sin(2B) - 7.53\cos(B) - 1.5\sin(B)$	Empirical correction for the eccentricity and obliquity of the Earth
Correction factor	$B = \frac{360}{365}(n-81)$	Correction factor
Time correction factor	$TC = 4(LON - LSTM) + EoT$	Correction factor to the local solar time to take into account the time zone effect, LON is the longitude of the given location
Local solar time	$LST = LT + \frac{TC}{60}$	Solar time at the given location, LT is the local time
Hour angle	$HRA = 15°(LST - 12)$	Conversion of the local solar time to the angular position of the sun during the day
Elevation angle	$\alpha = \arcsin(\sin(\delta)\sin(\varphi) + \cos(\delta)\cos(\varphi)\cos(HRA))$	Angle between the sun and the free horizon, φ is the latitude of the location

The sun's position, i.e. zenith and azimuth angle, can then be determined by:

$$\theta_s = 90° - \alpha$$

$$\phi_s = arccos\left(\frac{sin(\delta)\,cos(\varphi) - cos(\delta)\,sin(\varphi)\,cos\,(HRA)}{cos\,(\theta_s)}\right)$$

The resulting daily profiles for each of the seasons and locations are shown in figure S5. In order to implement these profiles in TIMES-Longyearbyen, we have converted the generation profiles into availability as a unit of installed nominal capacity rather than per area. According to the Norwegian Water Resources and Energy Directorate, there is an international agreeance to use a conversion factor of 0.7 kW_{th}/m^2 [16].

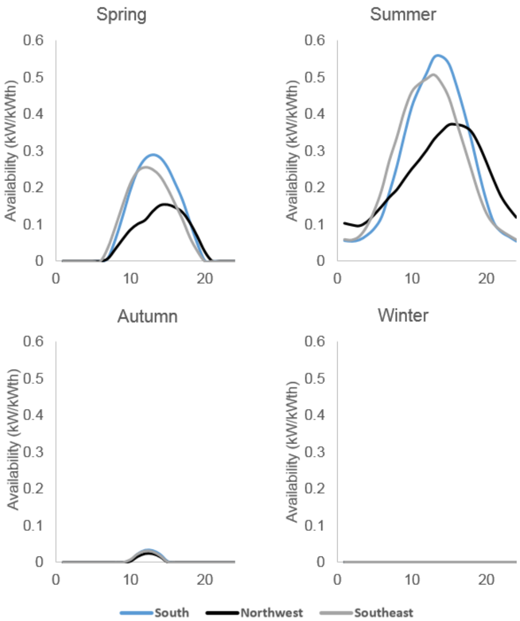


Figure S5: Daily profiles for solar thermal availability

Table S4: Average annual availability factors

	South, 30 ° tilt	Northwest, 20 ° tilt	Southeast, 20 ° tilt
Avg. annual availability factor (%)	8.98	7.18	8.57

Table S4 - Detailed results – installed capacities

Installed capacities (MW)

FOS	2015	2020	2025	2030	2035	2040	2045	2050
Coal (Back-pressure)	5.5	5.5	5.5					
Coal (Condensation)	5.5	5.5	5.5					
Diesel (Existing)	8.8	8.8	8.8					
Diesel (New)				2.0	2.0	2.0	2.0	2.6
Gas CHP				3.2	3.2	3.2	3.2	2.3
Gas Turbine				3.0	3.0	3.0	3.0	3.7
Solar PV - Existing	0.1	0.1	0.1	0.1	0.1			
Solar PV - Ground						0.7	0.7	0.9
Onshore wind		0.5	0.5	3.6	4.5	5.9	5.9	5.7
Electric boiler				1.0	1.2	2.5	3.1	2.4
Gas boiler				10.3	10.3	5.6	5.6	5.3
Heat pumps				0.3	0.5	1.5	1.2	1.0
Oil boiler	20.6	20.6	20.6					
Battery charge/discharge						0.1	0.1	0.1
Battery storage (GWh)						0.0	0.0	0.0

HYD	2015	2020	2025	2030	2035	2040	2045	2050
Coal (Back-pressure)	5.5	5.5	5.5					
Coal (Condensation)	5.5	5.5	5.5					
Diesel (Existing)	8.8	8.8	8.8					
Solar PV - Existing	0.1	0.1	0.1	0.1	0.1			
Solar PV - Ground				5.8	12.5	14.5	14.5	14.5
Onshore wind		0.5	0.5	18.1	22.7	22.1	23.7	20.5
Electric boiler				3.1	3.1	3.1	3.1	3.1
Heat pumps				10.6	10.6	10.6	8.4	6.8
Oil boiler	20.6	20.6	20.6					
Solar thermal							0.6	0.6
Battery charge/discharge				1.5	1.8	2.1	3.4	2.7
Hydrogen fuel cells				6.9	6.5	5.9	5.5	5.5
Hydrogen storage (MWh)				67.4	75.6	75.6	75.6	65.4
Battery storage (MWh)				6.3	8.9	13.7	17.3	14.8

ISO	2015	2020	2025	2030	2035	2040	2045	2050
Coal (Back-pressure)	5.5	5.5	5.5					
Coal (Condensation)	5.5	5.5	5.5					
Diesel (Existing)	8.8	8.8	8.8					
Solar PV - Existing	0.1	0.1	0.1	0.1	0.1			
Solar PV - Ground				103.1	103.1	103.1	103.1	109.6
Solar PV - Residential				16.8	16.8	16.8	16.8	16.8
Onshore wind		1.9	2.2	125.6	125.6	123.7	123.4	109.4
Electric boiler				3.1	3.1	3.1	3.1	1.8
Heat pumps				10.9	10.9	10.9	8.9	7.5
Oil boiler	20.6	20.6	20.6					
Battery charge/discharge				10.4	10.4	8.5	8.5	11.3
Hydrogen electrolyser (PEM)				8.2	6.5	6.9	10.7	5.5
Hydrogen fuel cells				4.2	3.4	4.0	4.0	3.1
Hydrogen storage (GWh)				30.8	30.8	30.8	30.8	21.9
Battery storage (MWh)				56.6	56.6	38.8	45.1	51.1

Table S5 - Detailed results – energy generation

Energy generation (GWh)

FOS	2015	2020	2025	2030	2035	2040	2045	2050
Coal (Back-pressure)[2]	19/74	18/74	18/73					
Coal (Condensation)	18.1	18.1	18.1					
Diesel (Existing)	2.6	0.00	0.00					
Diesel (New)				0.04	0.01	0.03	0.03	0.04
Gas CHP				13/34	11/30	10/28	10/25	8/22
Gas Turbine				6.1	5.7	5.1	5.8	7.2
Solar PV - Existing	0.06	0.06	0.06	0.06	0.06			
Solar PV - Ground						0.5	0.5	0.6
Onshore wind		1.2	1.2	7.6	9.7	12.8	12.6	12.2
Electric boiler				0.3	0.6	1.6	1.8	1.7
Gas boiler				16.3	14.2	8.0	7.2	7.3
Heat pumps				1.5	2.3	6.0	4.3	3.8
Oil boiler		0.0						
Battery charge/discharge						0.02	0.02	0.02

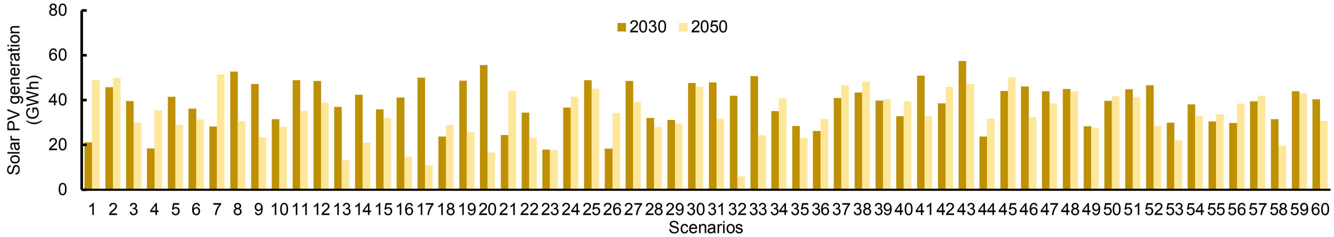
[2] (Electricity/heat)

HYD	2015	2020	2025	2030	2035	2040	2045	2050
Coal (Back-pressure)	19/74	18/74	18/73					
Coal (Condensation)	18.1	18.1	18.1					
Diesel (Existing)	2.6	0.00	0.00					
Solar PV - Existing	0.06	0.06	0.06	0.06	0.06			
Solar PV - Ground				1.0	2.9	3.5	2.7	2.5
Onshore wind		1.2	1.2	7.6	12.9	13.3	10.3	10.1
Electric boiler				6.7	10.0	9.3	7.3	6.3
Heat pumps				10.8	11.3	10.3	7.3	5.8
Oil boiler		0.0						
Solar thermal							0.2	0.2
Battery charge/discharge				0.4	0.8	1.2	1.1	1.1
Hydrogen fuel cells				34/34	26/26	23/23	23/23	22/22

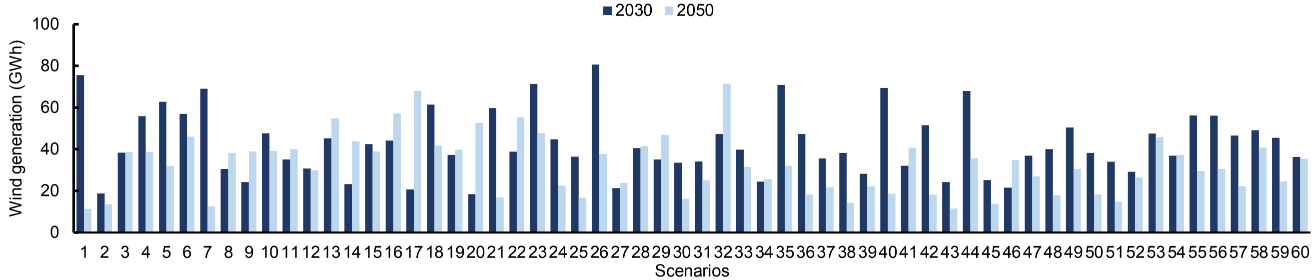
ISO	2015	2020	2025	2030	2035	2040	2045	2050
Coal (Back-pressure)	19/74	18/74	18/73					
Coal (Condensation)	18.09	18.09	18.09					
Diesel (Existing)	2.61	0.00	0.00					
Solar PV - Existing	0.06	0.06	0.06	0.06	0.06			
Solar PV - Ground				32.1	32.2	29.8	36.8	27.0
Solar PV - Residential				6.46	6.86	6.78	7.02	6.33
Onshore wind		4.08	4.82	42.7	34.2	36.5	37.1	32.3
Electric boiler				9.66	10.70	9.53	7.78	7.21
Heat pumps				24.5	22.1	21.2	17.0	14.9
Oil boiler		0.0						
Battery charge/discharge				10.6	10.3	7.9	9.0	8.9
Hydrogen electrolyser (PEM)				-51	-41	-42	-55	-38
Hydrogen fuel cells				11/11	8.7/8.7	9/9	12/12	8/8

Figure S6 – Scenario specific results (ISO)

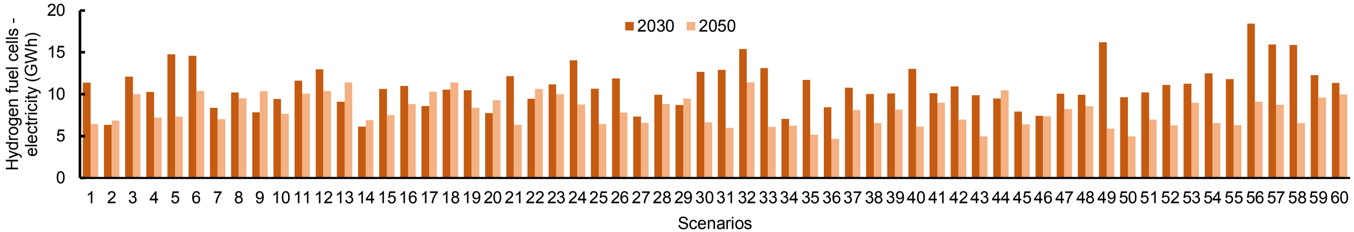
a) Solar PV generation



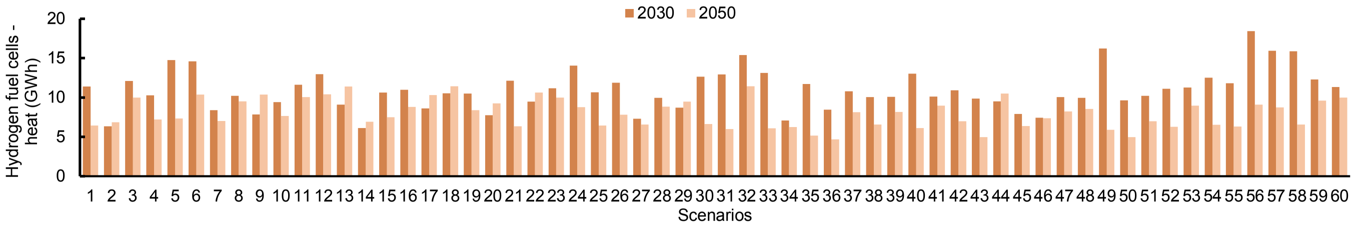
b) Onshore wind generation



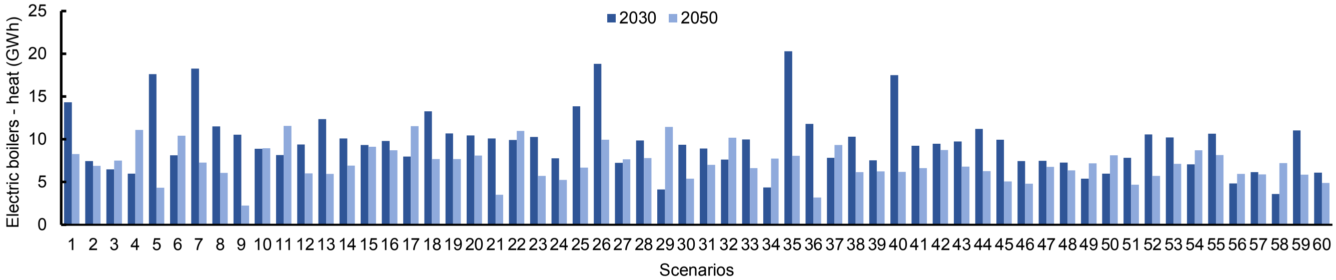
c) Electricity from hydrogen fuel cells



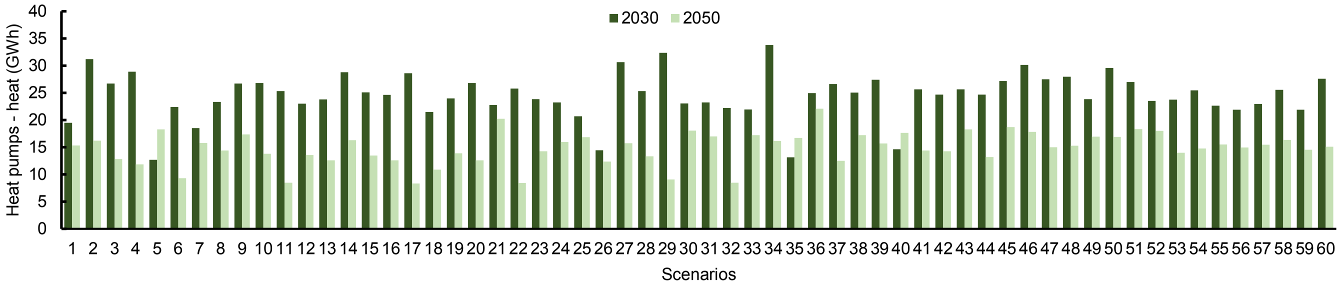
d) Heat from hydrogen fuel cells



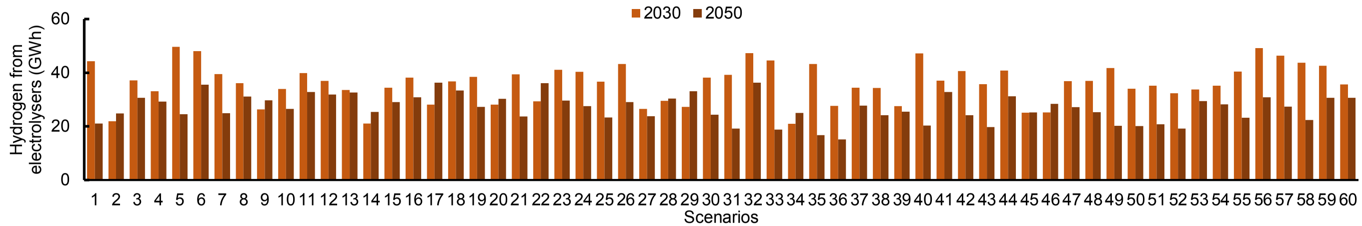
e) Heat from electric boilers



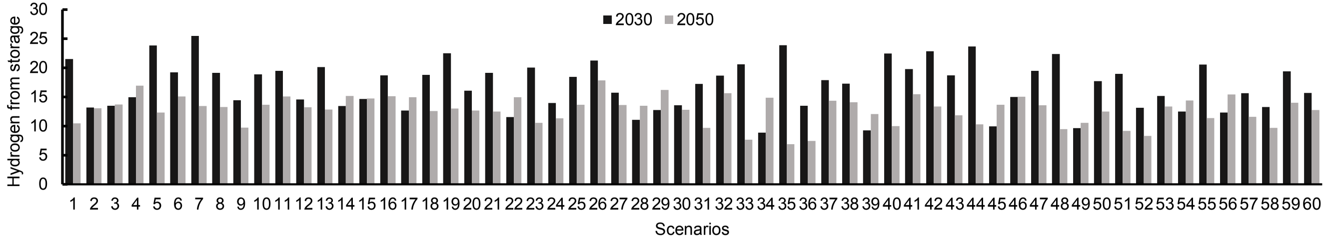
f) Heat from heat pumps



g) Hydrogen from electrolysers



h) Hydrogen from storage



i) Discharge from battery storage

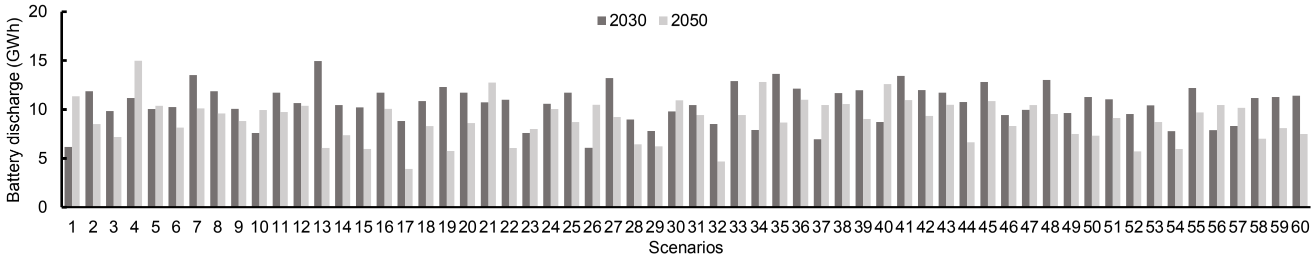
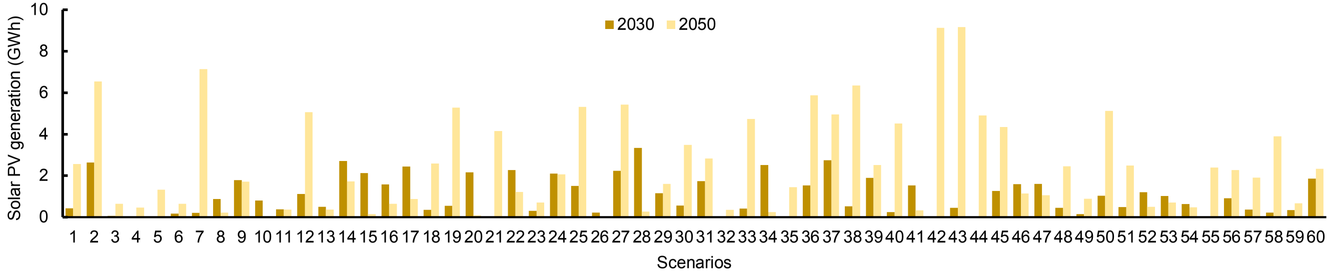
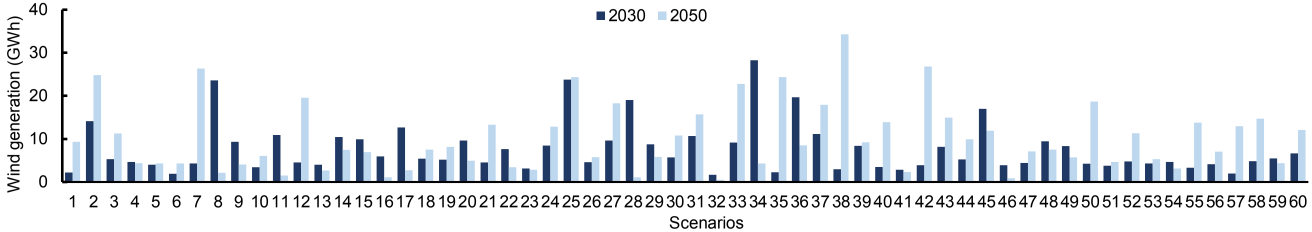


Figure S7 – Scenario specific results (HYD)

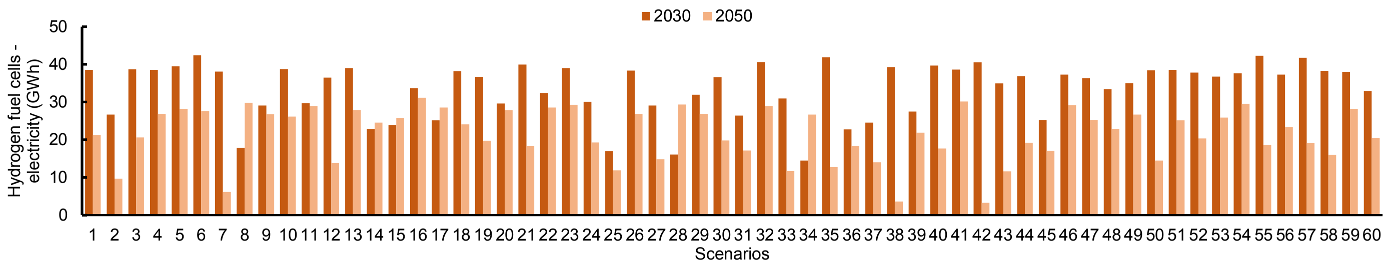
a) Solar PV generation



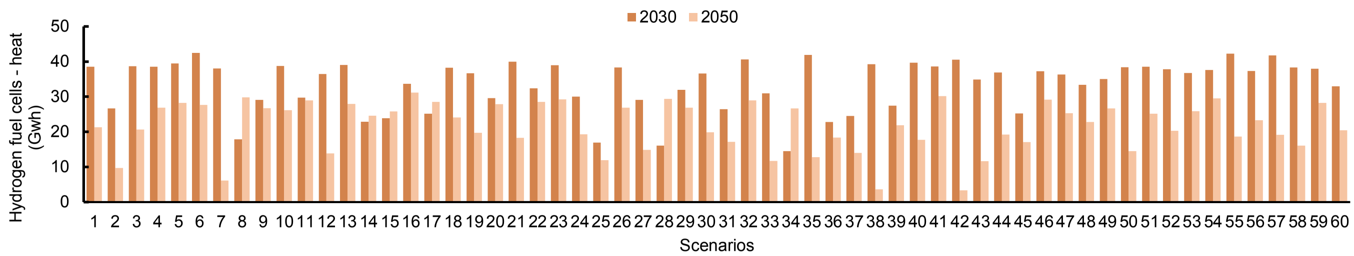
b) Onshore wind generation



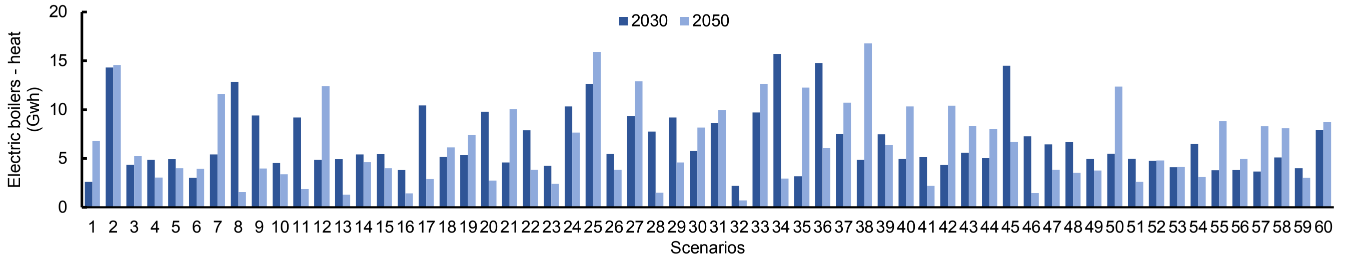
c) Electricity from hydrogen fuel cells



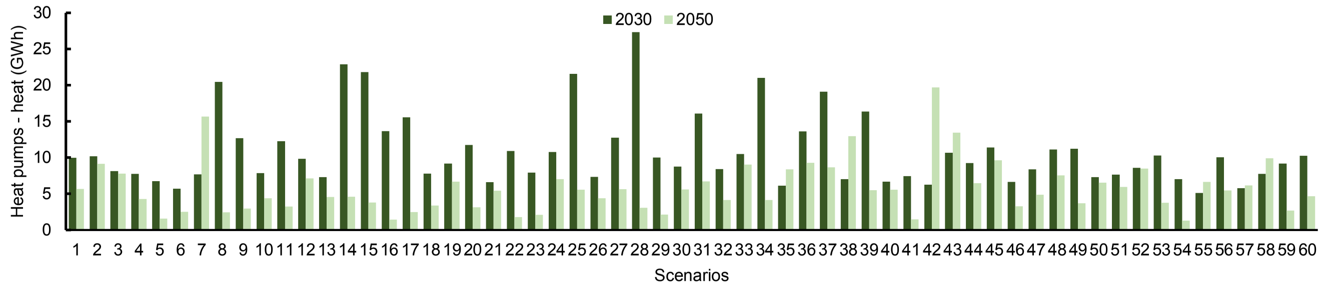
d) Heat from hydrogen fuel cells



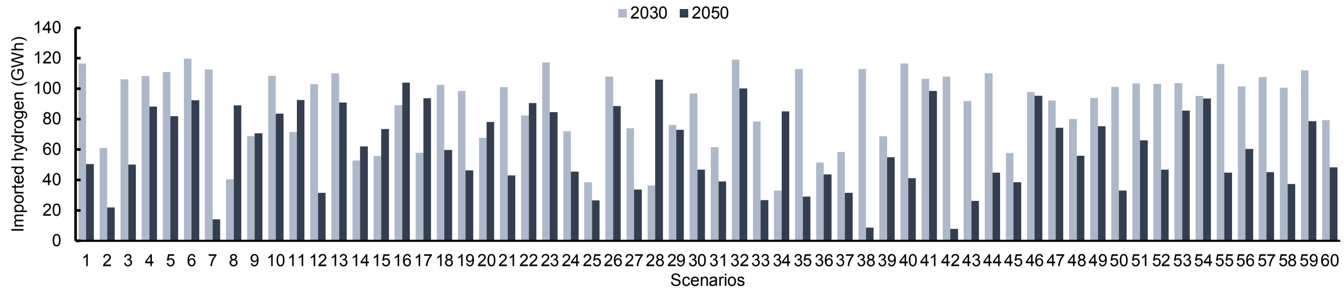
e) Heat from electric boilers



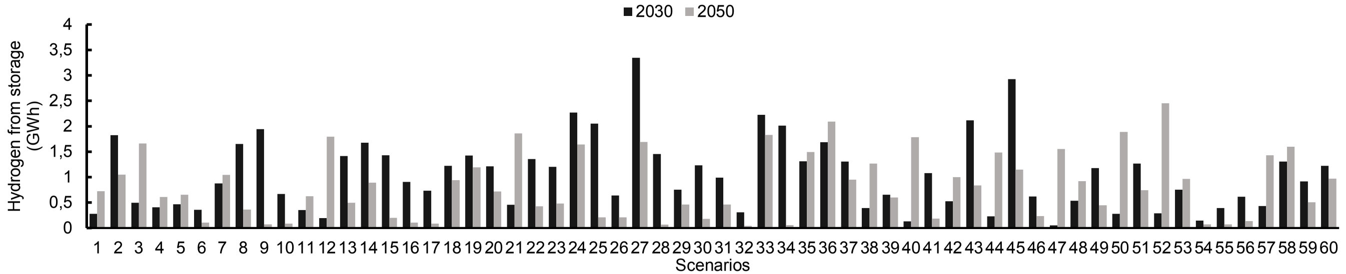
f) Heat from heat pumps



g) Imported hydrogen



h) Hydrogen from storage



i) Discharge from batteries

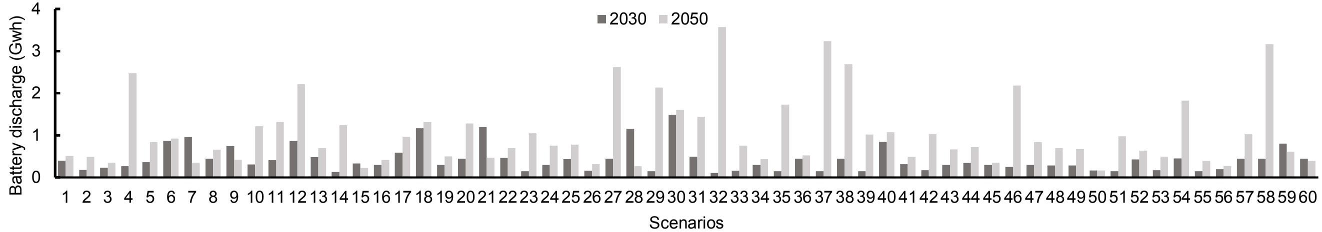
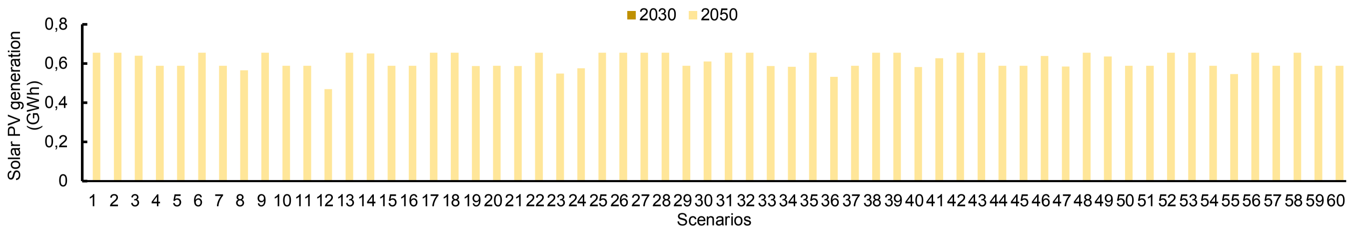
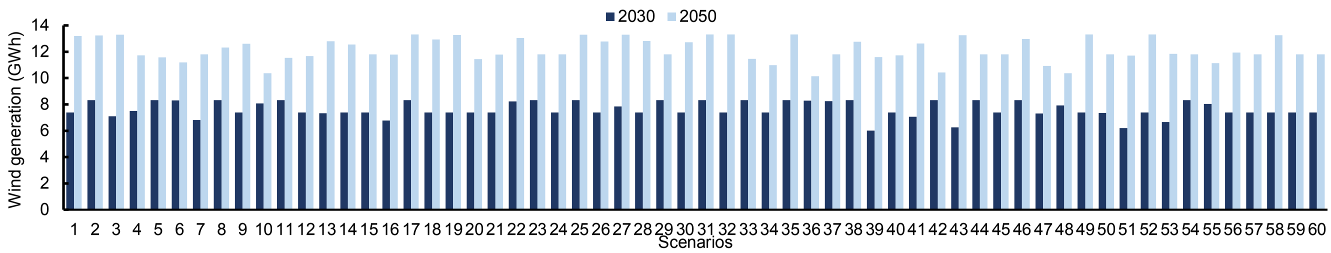


Figure S8 – Scenario specific results (FOS)

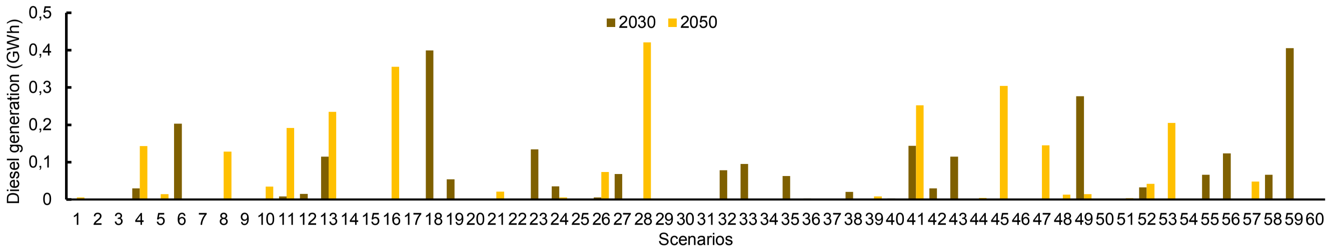
a) Solar PV generation



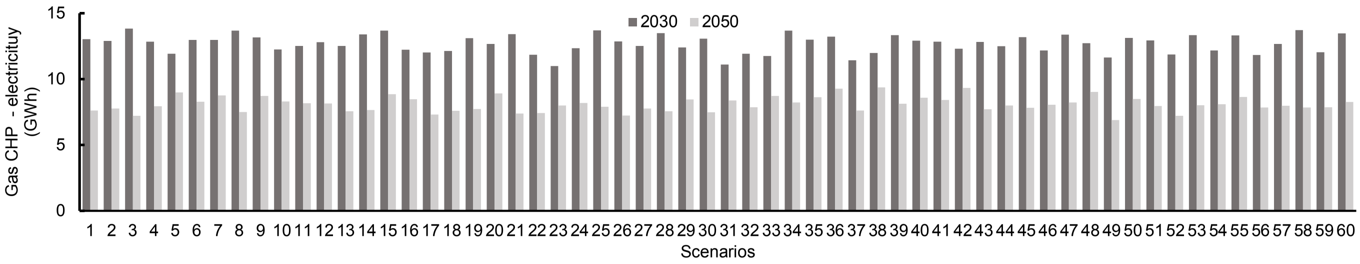
b) Onshore wind generation



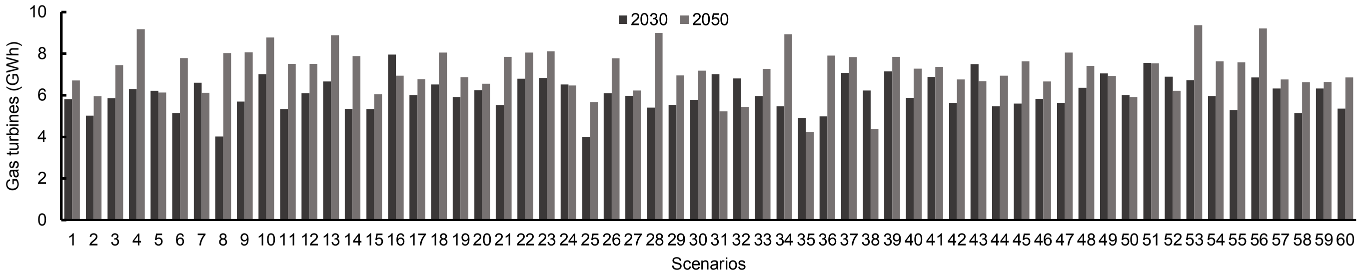
c) Diesel generation



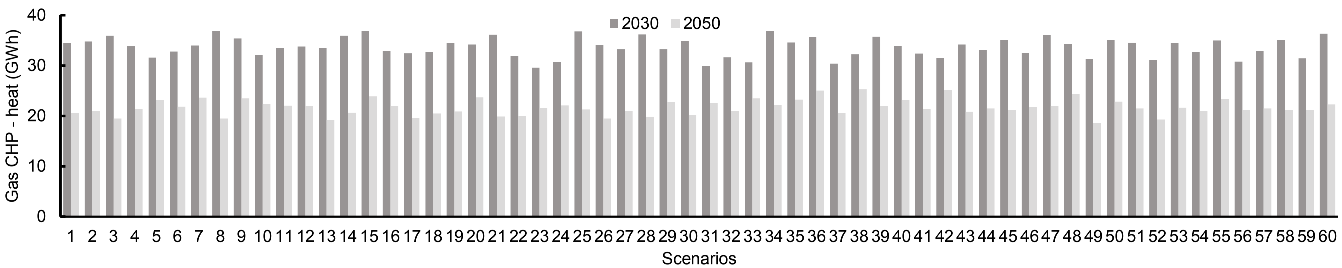
d) Electricity from gas CHP



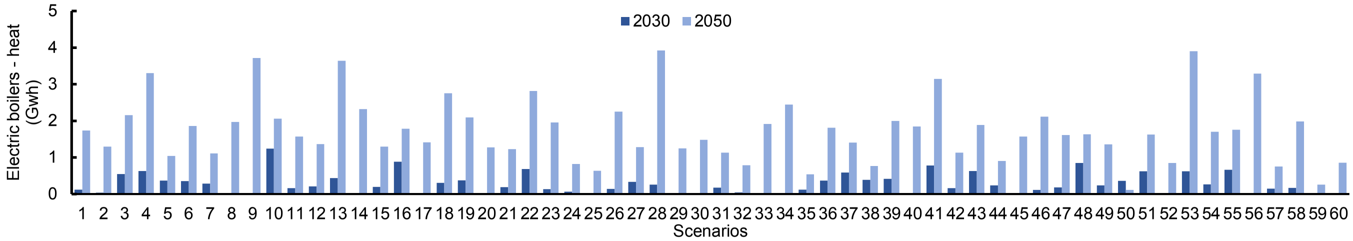
e) Gas turbine generation



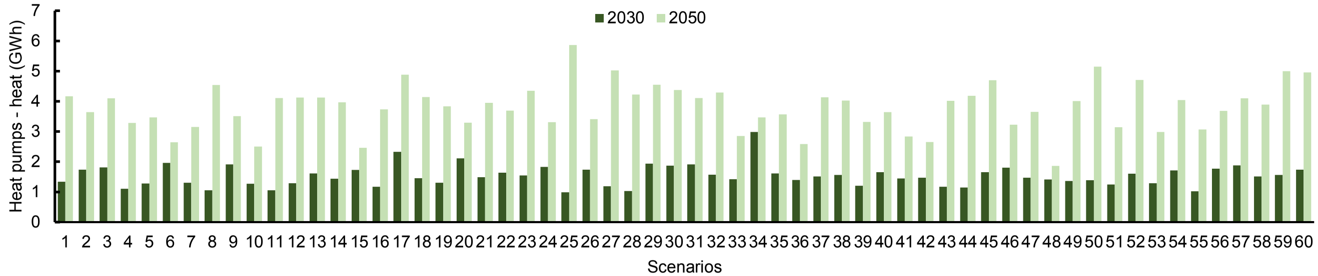
f) Heat from gas CHP



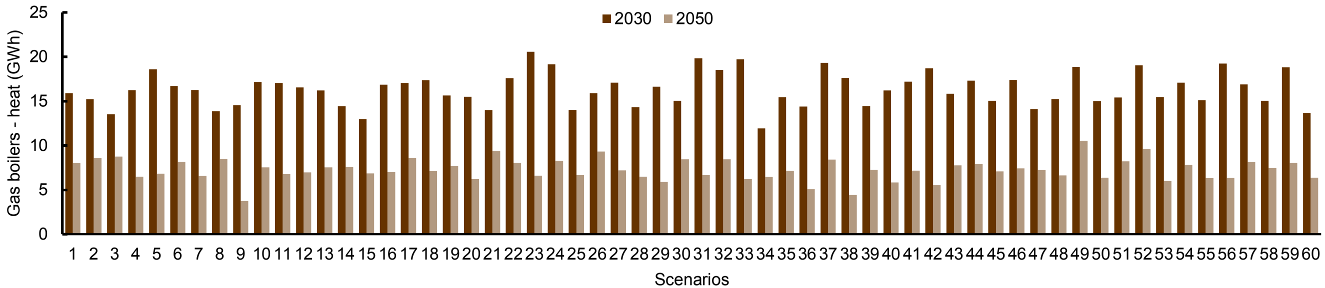
g) Heat from electric boilers



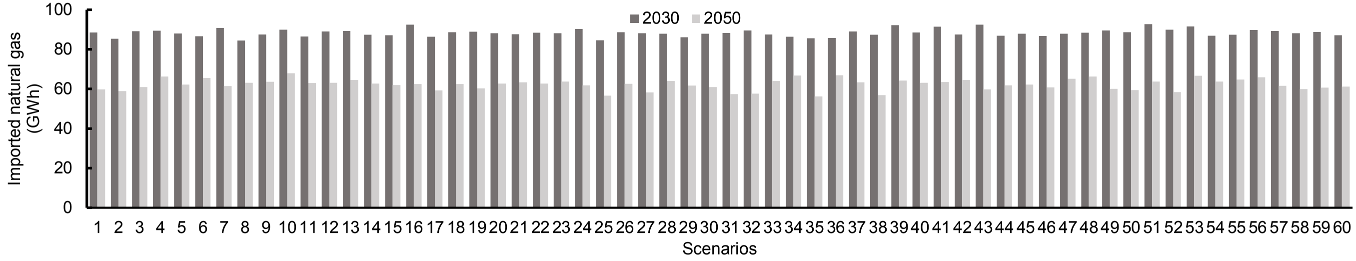
h) Heat from heat pumps



i) Heat from gas boilers



j) Imported natural gas



k) Discharge from batteries

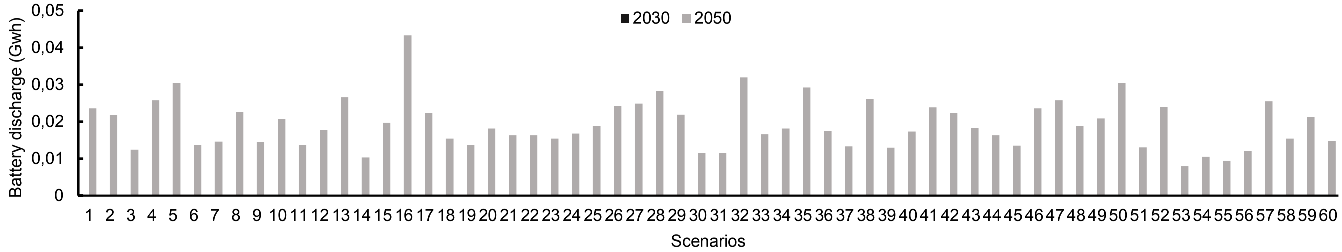
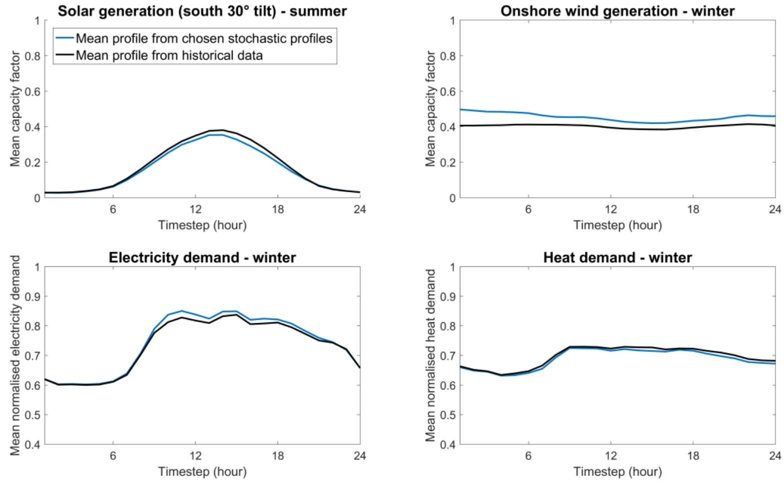
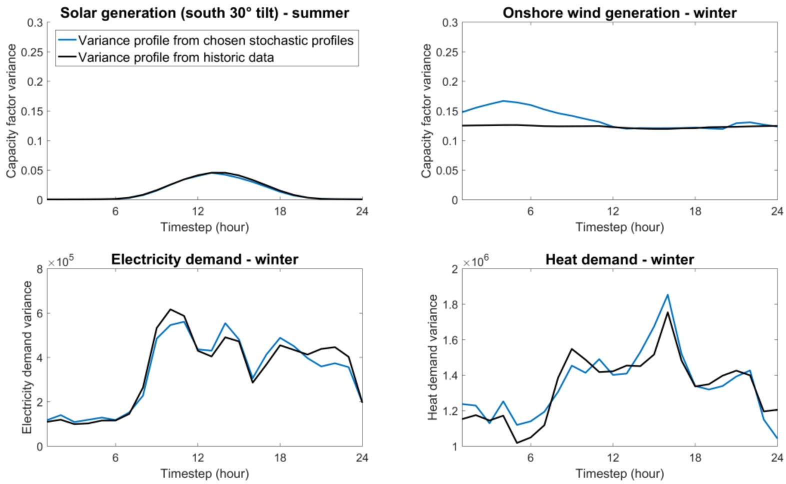


Figure S9 – Comparison of chosen stochastic profiles to historic profiles

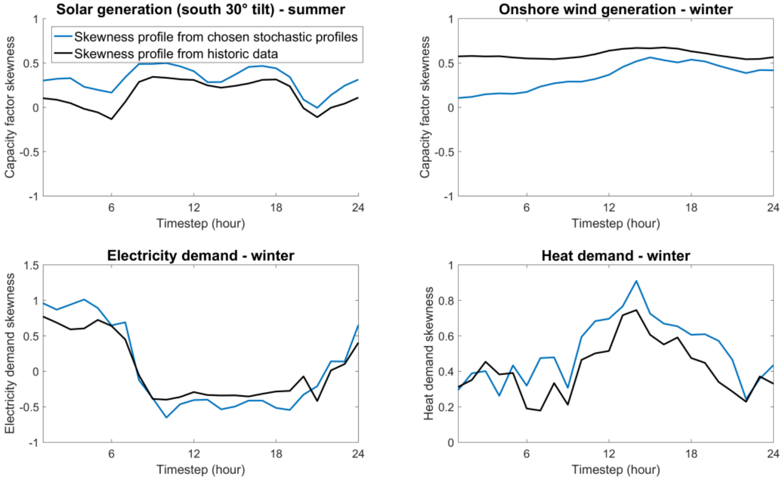
a) Comparison of mean profiles



b) Comparison of variance profiles:



c) Comparison of skewness profiles



d) Comparison of kurtosis profiles

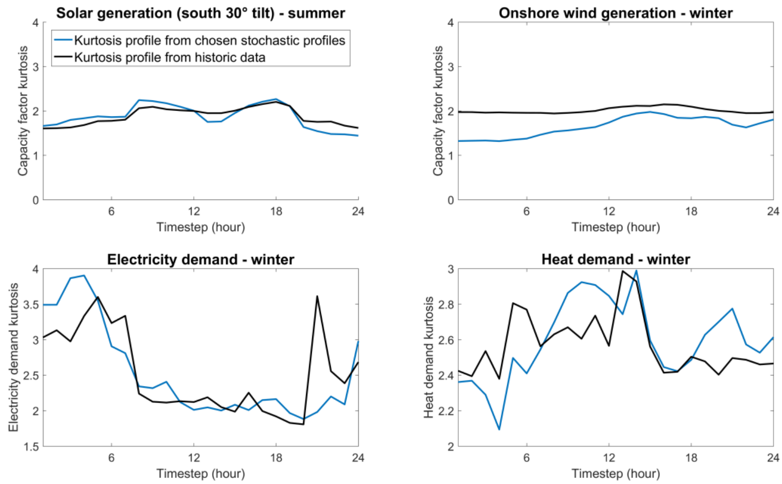


Figure S10 – Comparison of probability density functions for onshore wind and Solar PV generation

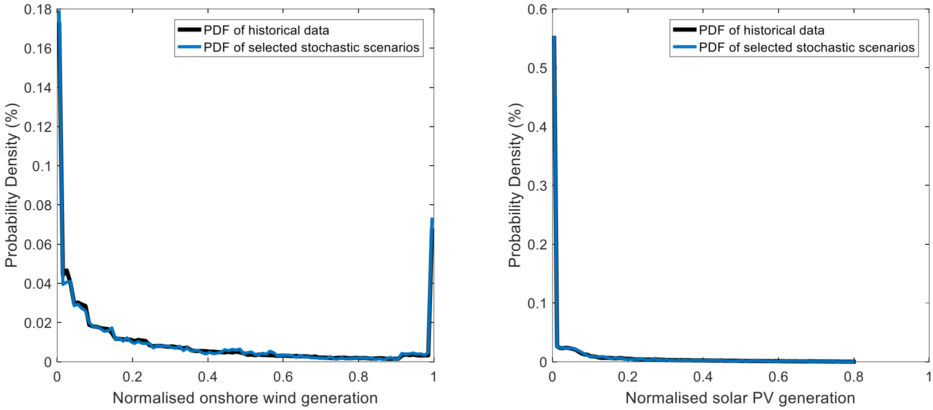


Figure S10 shows that the pdfs are very well captured by our scenario generation method. The figure also shows some interesting features of solar and wind generation. While pdfs of wind speed tend to follow the Weibull distribution, the pdf of the electricity generation is largely impacted by the wind turbine power curve (left panel). A wind turbine does not generate electricity below a given cut-in wind speed (3 m/s for the onshore wind turbine in our case), explaining the high probability density of zero electricity generation. Similarly, above nominal wind speed (12 m/s) the electricity generation is constant at rated power, thus explaining the increased probability density at a normalised generation of 1.

The pdf of solar PV generation (right panel) is largely impacted by nighttime and the polar night, which leaves Longyearbyen without any sunlight for large portions of the year and leads to a very high probability density of no solar PV generation. Furthermore, solar PV generation is characterised by a relatively regular diurnal behaviour, with peak generation being achieved at solar noon. Due to the peak power of solar PV panels being registered under Standard Test Conditions (1000 W/m^2, 25 °C cell temperature and 1.5 AM), such power levels are not reached in Longyearbyen.

Figure S11 – Comparison of autocorrelation function for onshore wind and solar PV generation in the 192 time-slice model

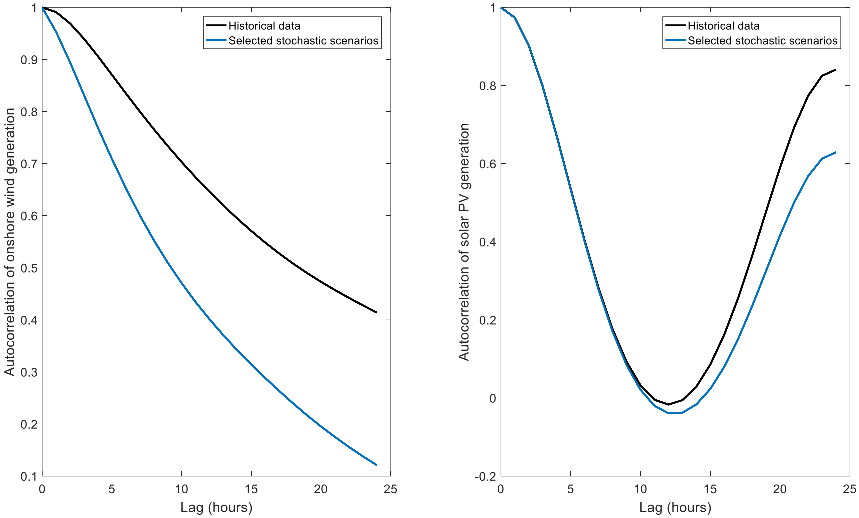
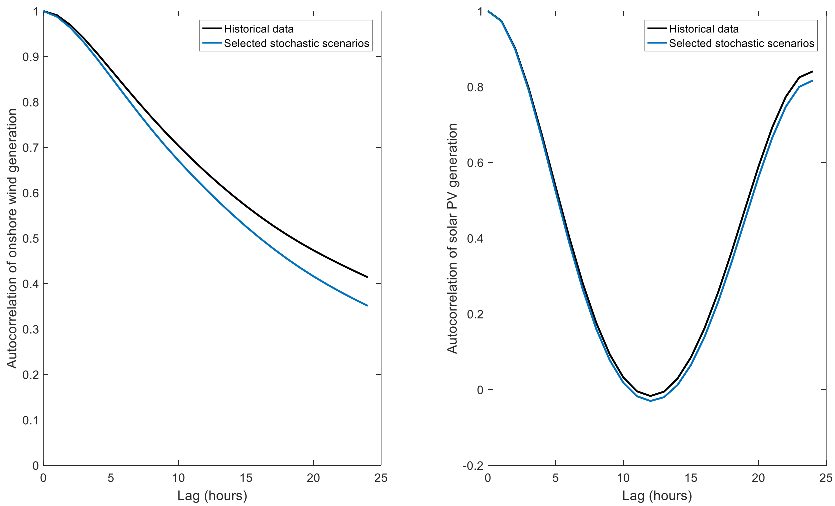


Figure S12 – Comparison of autocorrelation function for onshore wind and solar PV in the 672 time-slice model



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Appendix B

Supplementary material to Paper III

Supplementary material

Representation of short-term solar and wind variability in long-term energy models - a European case study

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1. TIMES-Europe

1.1. Overall Structure

TIMES-Europe focuses on the European power and district heating systems. It covers 29 regions/countries in Europe, each represented as one node in the model network. The countries included are the EU-28 countries plus Norway and Switzerland, with the exception of Cyprus and Iceland as they presently are not connected to the European power system. All included countries are listed together with their abbreviations in Supplementary Table S1.

The base-year of the model is chosen as 2015, and the horizon is 2050. The discount rate is set to 4 %, based on recommendations from the Norwegian government in socioeconomic studies [1].

Supplementary Table S1: Countries included in TIMES-EUROPE

Country	Code	Country	Code	Country	Code
Austria	AT	France	FR	The Netherlands	NL
Belgium	BE	Greece	GR	Norway	NO
Bulgaria	BG	Croatia	HR	Poland	PL
Switzerland	CH	Hungary	HU	Portugal	PT
Czech Republic	CZ	Ireland	IE	Romania	RO
Germany	DE	Italy	IT	Sweden	SE
Denmark	DK	Lithuania	LT	Slovenia	SI
Estonia	EE	Luxembourg	LU	Slovakia	SK
Spain	ES	Latvia	LV	United Kingdom	UK
Finland	FI	Malta	MT		

1.2. Demand Projections

Future projections of electricity and district heat demand are supplied exogenously to TIMES-Europe, and are one of the most important drivers of model results. All demand projections for the EU-28 countries are retrieved from the European Commission's Reference Scenario 2016 [2]. Norway's demand projections are based on statistics and projections from Norwegian authorities for 2030 ([2–4]), fitted to the demand growth seen in Sweden in the EU Reference Scenario. The same procedure was followed in the case of Switzerland (based on [5–7]), using the relative growth in Austria as reference.

Supplementary Table S2 and S3 show the electricity and district heat demand projections per country towards 2050. The aggregated electricity demand increases by 25 % between 2015 and 2050, whereas the district heat demand increases by 8 %.

Supplementary Table S2: Electricity demand projection per country

	2015	2020	2025	2030	2035	2040	2045	2050
AT	63.2	67.2	69.7	72.5	74.7	77.7	81	82.8
BE	81.8	84	85.4	89	91.9	97.3	103.9	108.1
BG	27.7	29.1	30.2	31.1	31.7	32.8	34	35.6
CH	63.4	66.3	68.8	70.8	72.7	75.2	78.6	81.6
CZ	58.3	61	64.1	66.1	68.9	71.8	75.7	79.1
DE	522	530	545	559	562	566	573	580
DK	31.8	32.8	34.5	35.7	37.8	39.8	42.2	44.5
EE	7.1	7.6	7.9	8.3	8.6	8.9	9.4	9.8
ES	233	247	249	257	263	270	279	291
FI	78.9	79.7	82.4	83.9	86.3	88.8	92.6	96.1
FR	439	452	458	469	489	509	527	548
GR	51.1	53.3	52	50.5	52.9	54.3	55.2	56.4
HR	15.3	16.2	16.2	16.4	17.1	17.9	19.1	20.5
HU	34.6	35.9	38.2	39.1	40.6	42.9	45.6	47.2
IE	24.5	26.2	27.3	28.1	29.3	30.6	32.1	33.9
IT	294	304	306	314	336	359	378	395
LT	9.7	10.3	10.4	10.2	10.3	10.5	11.2	11.7
LU	6.5	6.9	7.5	8.3	9.3	10.4	11.3	12
LT	6.6	7.2	7.6	8.1	8.5	9	9.5	9.9
MT	1.9	2.3	2.5	2.6	2.6	2.8	3	3.1
NL	105	111	114	116	119	123	127	133
NO	123	129	133.4	132	135	139	146	151
PL	128	142	156	168	177	186	194	202
PT	45	47.1	47.7	47.8	48.5	49.6	50.5	51
RO	42.8	47.2	49.2	51.1	53.3	56.3	59.4	62.3
SE	129	135	140	144	148	153	160	166
SL	12.8	13.5	14.7	15.1	15.4	16	16.6	17.2
SK	25.8	27.1	29.4	31.1	32.2	33	33.7	34.2
UK	322	335	341	356	372	395	421	438
Total	**2984**	**3106**	**3188**	**3281**	**3394**	**3526**	**3670**	**3801**

Supplementary Table S3: District heat demand projection per country

	2015	2020	2025	2030	2035	2040	2045	2050
AT	23.4	22.2	23.8	24.9	25.2	25.7	25.7	25.0
BE	6.6	7.1	7.9	8.6	9.2	10.0	10.5	10.9
BG	9.8	10.1	10.8	11.2	10.7	10.7	10.6	10.6
CH	5.1	5.6	6.1	6.6	6.6	6.8	6.8	6.6
CZ	24.4	26.6	28.1	28.4	28.8	28.9	28.6	29.0
DE	115.0	114.0	120.0	122.0	116.0	119.0	120.0	118.0
DK	29.7	29.2	29.1	29.9	29.8	29.4	28.9	29.6
EE	5.6	6.0	6.0	6.1	6.2	6.2	6.2	6.2
ES	0.1	1.4	3.5	6.8	8.5	10.2	8.8	8.5
FI	48.2	50.2	49.0	45.8	44.4	44.3	44.7	45.6
FR	42.5	39.6	40.7	41.0	43.9	45.5	46.2	46.8
GR	0.5	0.6	0.7	0.8	1.0	1.2	1.1	1.2
HR	2.6	2.8	3.0	3.2	3.3	3.6	3.7	3.7
HU	11.5	11.7	10.8	11.8	11.0	11.2	11.8	12.0
IE	0.0	0.2	0.4	0.7	1.0	1.3	1.2	1.3
IT	41.8	44.2	45.4	45.7	42.3	43.4	42.5	42.8
LT	10.1	10.6	10.8	9.9	9.1	9.2	9.2	9.1
LU	0.9	0.9	0.9	0.9	0.9	0.9	1.0	1.0
LT	6.1	6.7	6.7	6.7	6.6	6.6	6.9	6.8
MT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
NL	23.7	25.1	26.9	28.6	27.9	29.0	29.4	29.4
NO	4.8	4.8	5.0	4.9	5.1	5.2	5.5	5.8
PL	70.5	80.8	79.3	91.3	97.3	106.0	105.0	106.0
PT	3.8	4.3	3.9	5.5	4.8	4.7	4.3	4.2
RO	17.4	18.9	20.0	20.9	21.8	22.7	23.8	24.7
SE	51.4	51.4	53.1	51.8	53.8	55.7	58.7	61.3
SL	2.3	2.4	2.5	2.5	2.5	2.5	2.5	2.5
SK	8.4	9.5	9.6	9.4	9.2	9.0	8.8	8.7
UK	14.7	15.6	16.3	17.8	18.7	15.3	14.3	15.2
Total	**608**	**603**	**620**	**644**	**646**	**664**	**667**	**673**

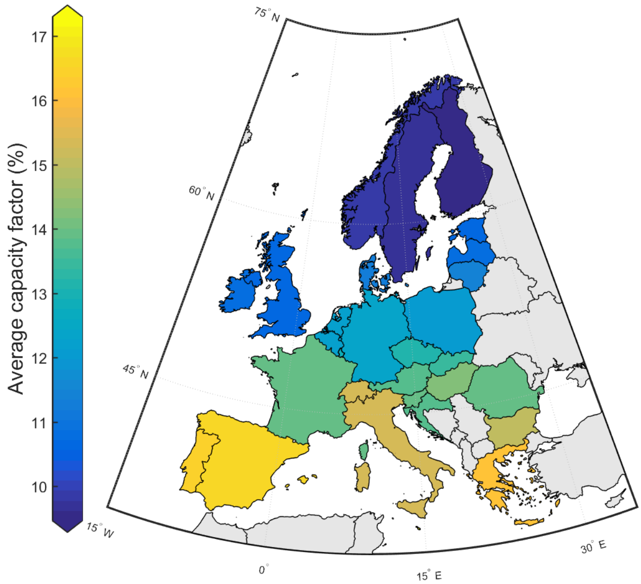
2. Input data

2.1. Solar and wind data

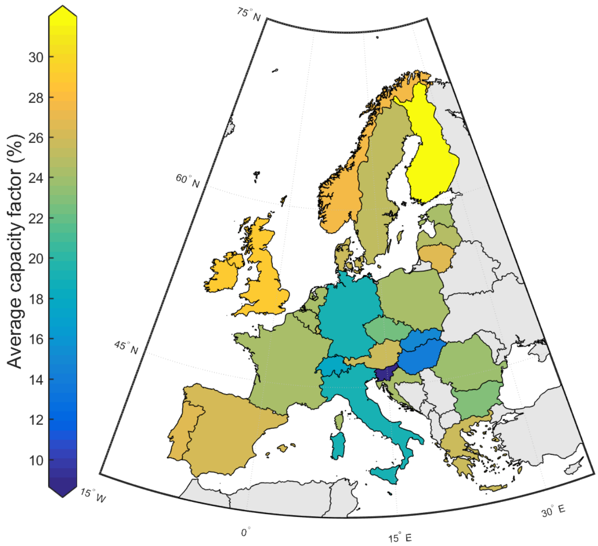
We have used 30 years of hourly solar and wind availability data (capacity factors), spanning from 1985 – 2015. These datasets are obtained from renewables.ninja, a web application based on the Global Solar Energy Estimator (GSEE) model and the Virtual Wind Farm (VWF) model [8,9].

Supplementary Figure S1, S2 and S3 show maps of the average national capacity factors for the whole 30-year period for solar, onshore wind and offshore wind respectively. The maps show that there are large geographical variations within Europe.

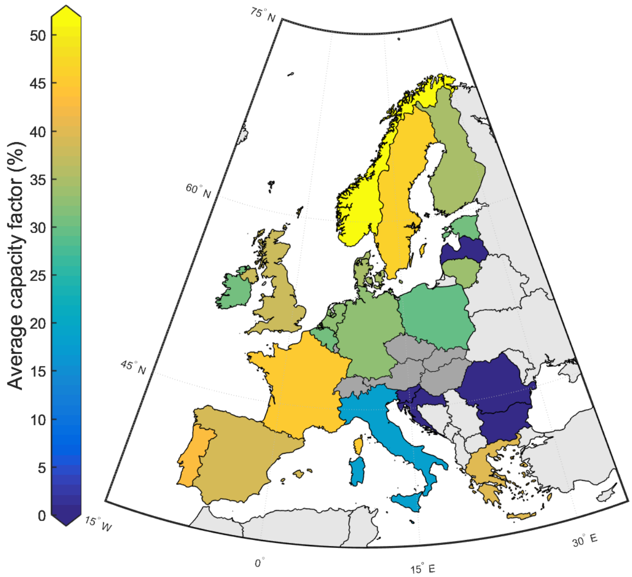
Currently Malta has no onshore wind capacity installed, and no wind data was thus available. Due to Malta's proximity to Italy, we have assumed the onshore wind capacity factor for Malta to be equal to that of Italy. In addition, Slovenia has only about 6 MW installed capacity of onshore wind power, with an annual capacity factor of only 8.6 %. Even though they have no current plans to build more onshore wind in Slovenia, this capacity factor could easily be increased in the future. For the long-term data, the annual capacity factor from Hungary is therefore used to scale the hourly production curve from Slovenia.



Supplementary Figure S1: Average national solar PV capacity factor



Supplementary Figure S2: Average onshore wind capacity factor



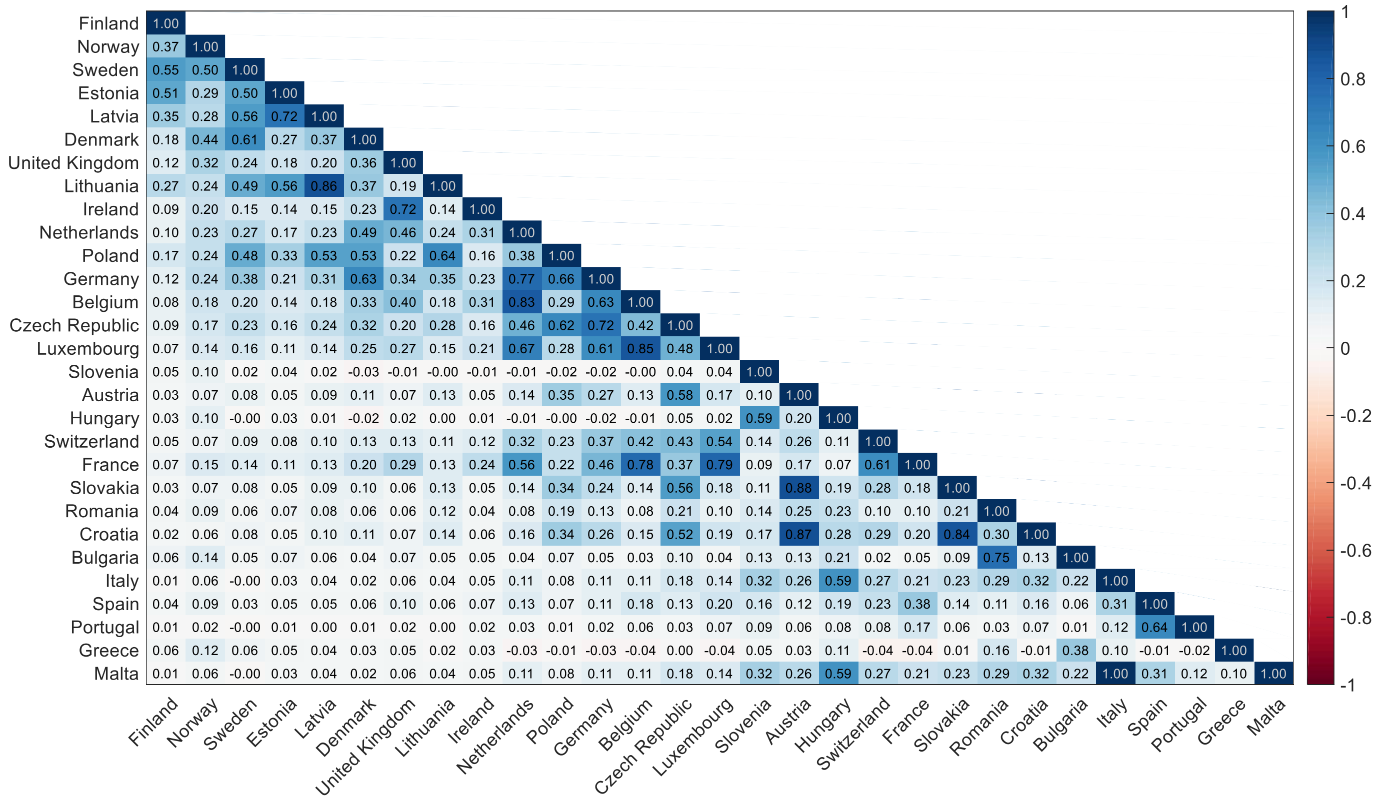
Supplementary Figure S3: Average offshore wind capacity factor

A future highly interconnected Europe could benefit from the smoothing effect seen when aggregating solar and wind generation over large geographical areas [10].

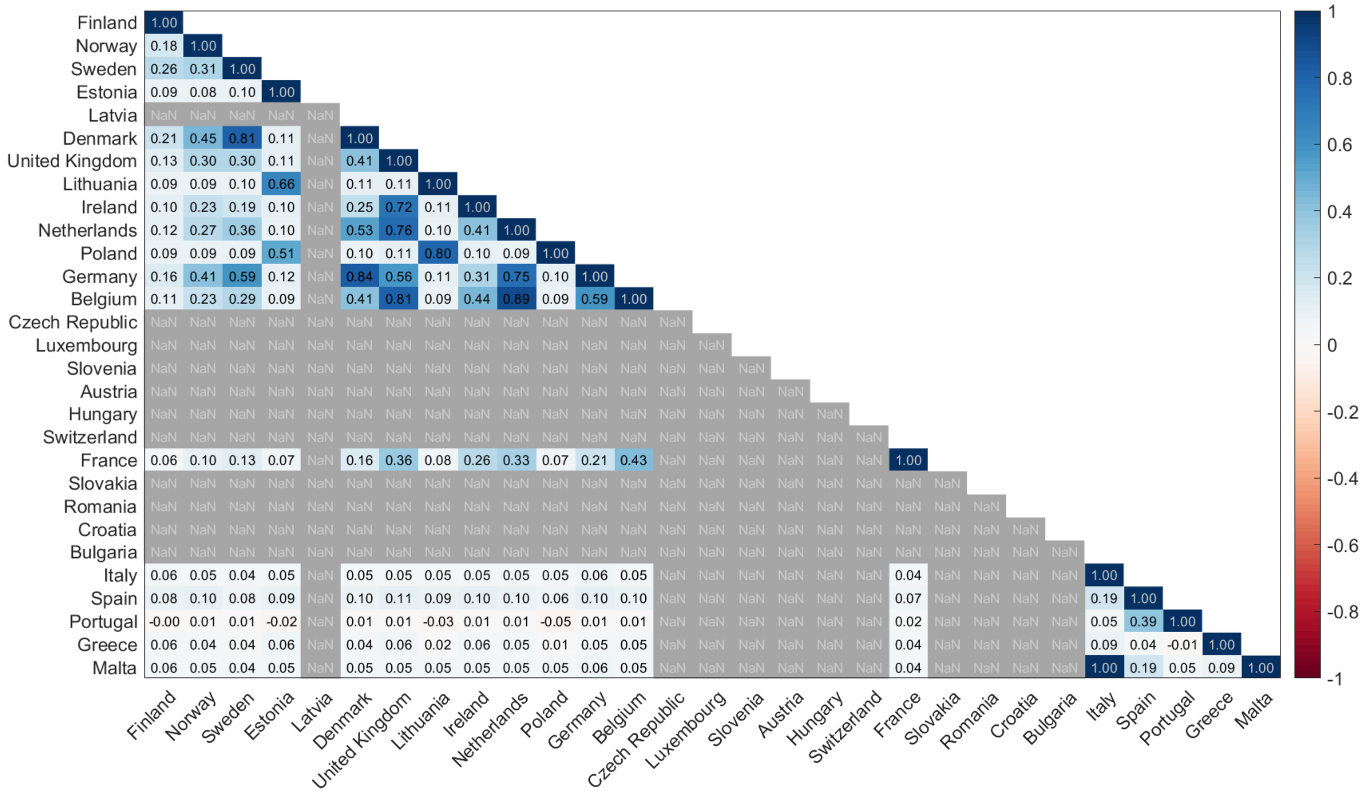
Supplementary Figure S4 and S5 show the Spearman rank correlation coefficients for respectively onshore and offshore wind generation in the 29 countries in TIMES-Europe, based on 30 years of hourly data. The countries are sorted by latitude, which shows that the correlation coefficients are generally higher for neighbouring countries or countries in close proximity. As an example, wind generation in Latvia and Lithuania shows a strong correlation (0.86), whereas the correlation between e.g. Latvia and Portugal is very low (0.00). Note that the correlation between Italy and Malta is 1.00 in the onshore and offshore wind cases, since, as already mentioned, the Italian data is used for Malta.

Because of the easy recognisable shape of solar generation, with a peak during solar noon, the Spearman rank factors for solar PV are generally high (note that the correlation factors for solar PV also includes nighttime, which increases the correlation factors).

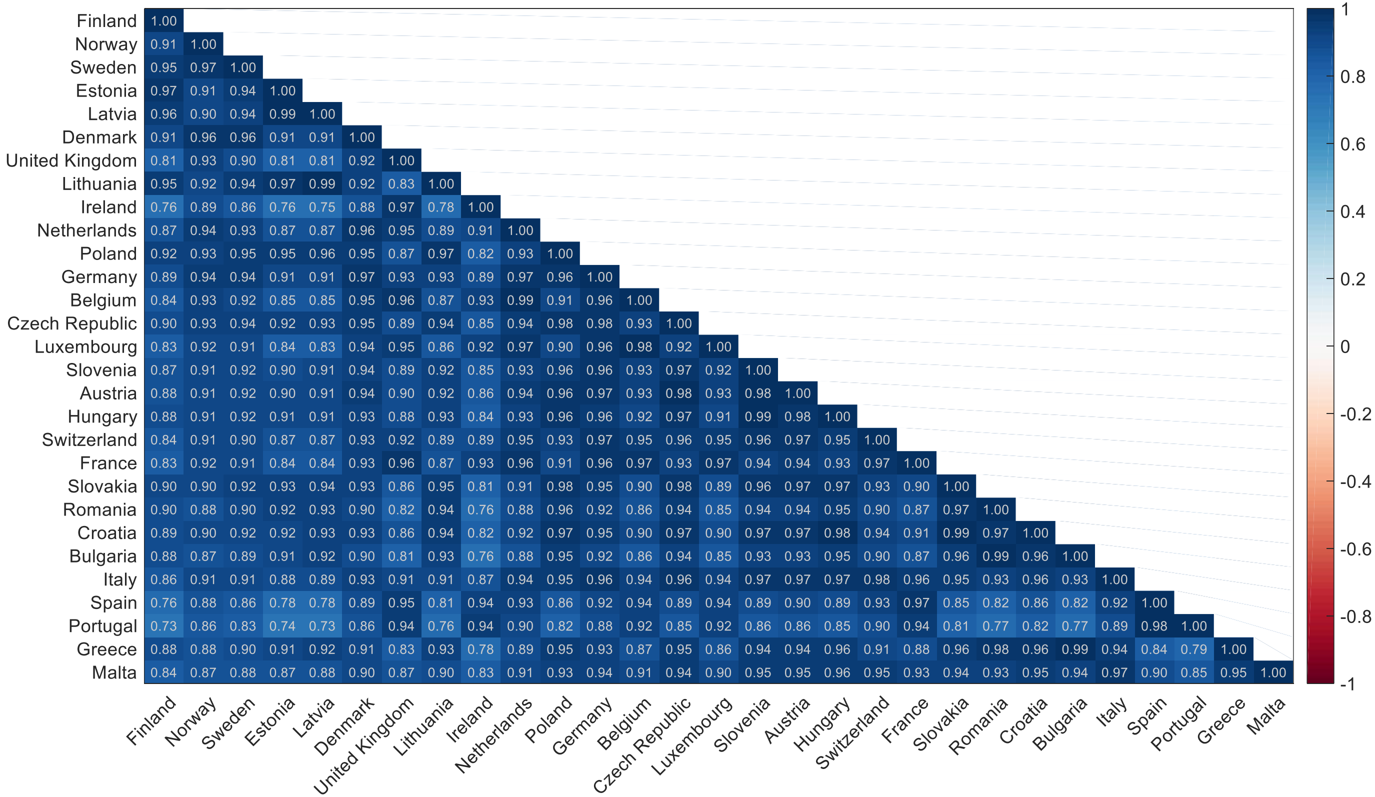
Since high wind speeds usually occur during cloudy skies and low solar irradiance, wind speed and solar radiation are somewhat negatively correlated. Supplementary Figure S7 shows the correlation coefficients between wind and solar generation, which is negatively correlated in almost all cases.



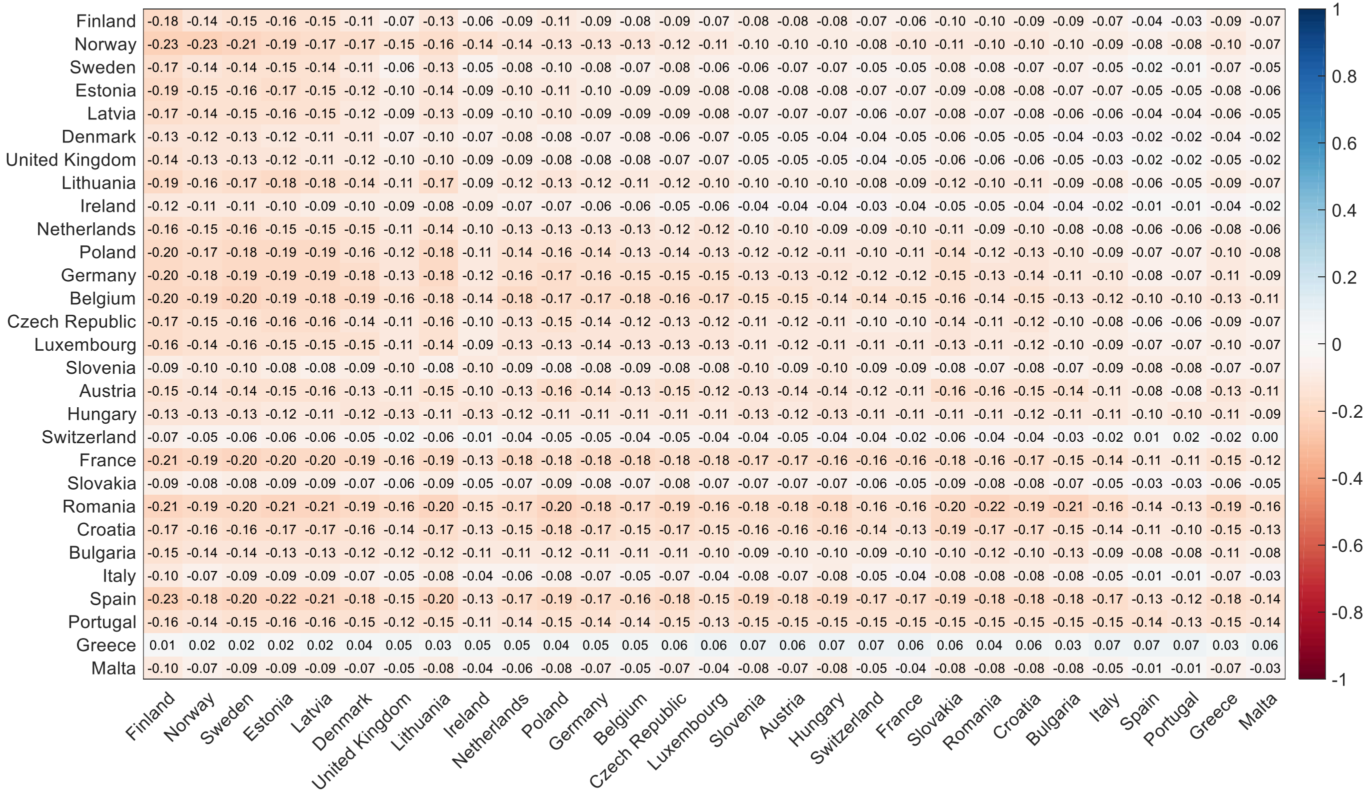
Supplementary Figure S4: Correlation matrix for onshore wind generation



Supplementary Figure S5: Correlation matrix for offshore wind generation



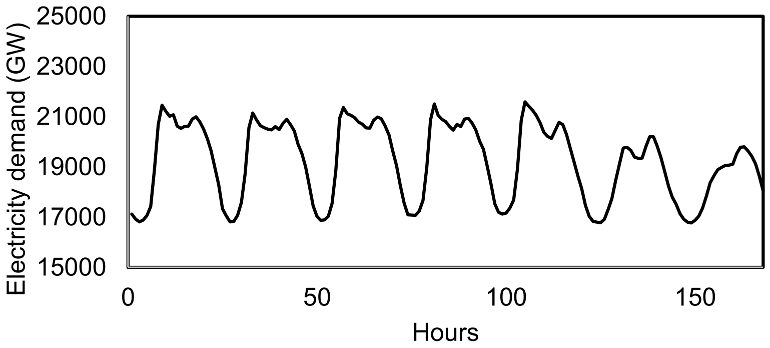
Supplementary Figure S6: Correlation matrix for solar PV generation



Supplementary Figure S7: Correlation matrix for onshore wind and solar PV generation

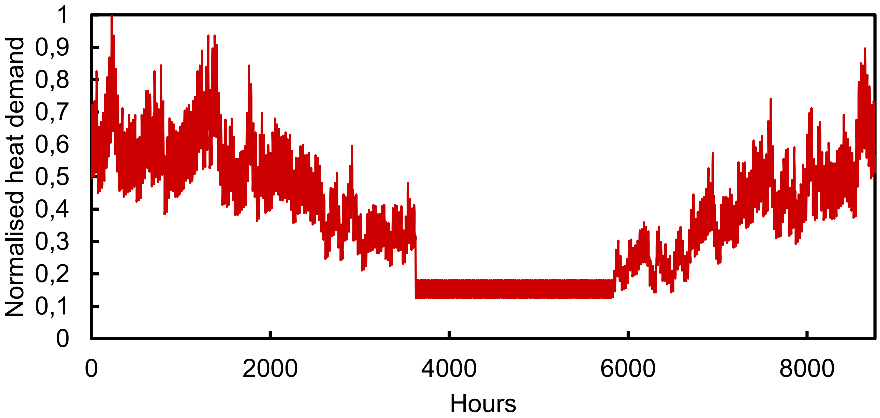
2.2. Load data

The hourly load of electricity is based on real data for all 29 countries from the European Network of Transmission System Operators for Electricity (ENTSO-E). We have used six years of hourly data between 2010 and 2015 to provide load profiles used in TIMES-Europe. Figure S8 shows an example of a representative load profile for a typical winter-day in Norway. The load data is also used to generate load profiles for the stochastic scenarios.



Supplementary Figure S8: Example of week of electricity demand in Norway (18.24. January 2010)

The load profile for heat demand is based on a generic profile based on EnergyPlan [11], shown in Supplementary Figure S9, and is used for all model regions in TIMES-Europe. This profile is scaled down to representative profiles used in the models with lower temporal resolution.



Supplementary Figure S9: Hourly heat demand profile from EnergyPlan

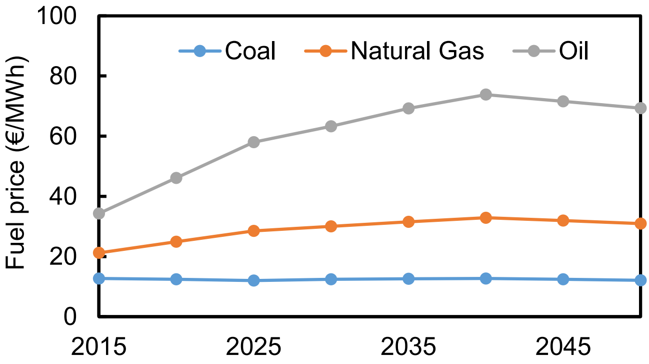
3. Technological parameters and cost assumptions

This chapter gives an overview of the various energy resources and technologies modelled in TIMES-Europe, their technological parameters and cost assumptions.

Currency conversions and inflation figures are retrieved from Norges Bank [12,13], and are used to convert costs to Euros and to the base year of 2015 when necessary.

3.1. Fossil Fuels

Import prices for coal, natural gas and oil from 2010 to 2050 are shown in Supplementary Figure S10 and Supplementary Table S4, and are based on the New Policies Scenario from the World Energy Outlook 2018 [14].



Supplementary Figure S10: Fossil fuel price assumptions

Supplementary Table S4: Fossil fuel import prices

€/MWh	2015	2020	2025	2030	2035	2040	2045	2050
Coal	12.7	12.4	12.0	12.4	12.6	12.7	12.4	12.1
Natural Gas	21.2	24.9	28.5	30.0	31.5	32.9	31.9	31.0
Oil	34.3	46.1	58.0	63.3	69.2	73.8	71.5	69.3
CO_2 (€/ton)[1]	7.7	16.4	25	31	37	43	49	55

CO_2 emissions related to the use of fossil fuels are reported on the import processes of the respective fuels. We have assumed emission factors of 340 tonne CO_2/GWh for coal, 202 tonne CO_2/GWh for natural gas, and 264 tonne CO_2/GWh for oil.

[1] The CO_2 price in 2015 is based on [72], and the projection towards 2040 is based on the New Policies Scenario from the World Energy Outlook 2018 and extrapolated to 2050.

3.1.1. Conventional generators

The tables below show the technological parameters and costs assumed for conventional fossil-based generators.

Supplementary Table S5: Techno-economic assumptions for coal-fired power plants

Coal-fired Power Plant	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency (%)	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	[15]
Availability Factor	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	[15]
Investment Cost (k€/MW)	1670	1670	1670	1670	1670	1670	1670	1670	1670	[15]
O&M Cost (k€/MW)	42	42	42	42	42	42	42	42	42	[15]
Variable Cost (ex. Fuel) (k€/GWh)	3.75	3.75	3.75	3.75	3.75	3.75	3.75	3.75	3.75	[15]
Technical Lifetime (years)	40	40	40	40	40	40	40	40	40	[15]

Supplementary Table S6: Techno-economic assumptions for combined cycle gas power plants

Gas power plant (CCGT)	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency (%)	0.58	0.6	0.62	0.62	0.62	0.62	0.62	0.63	0.63	[15]
Availability Factor	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	[15]
Investment Cost (k€/MW)	887	887	887	887	887	887	887	887	887	[15]
O&M Cost (k€/MW)	22.2	22.2	22.2	22.2	22.2	22.2	22.2	22.2	22.2	[15]
Variable Cost (ex. Fuel) (k€/GWh)	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	[15]
Technical Lifetime (years)	30	30	30	30	30	30	30	30	30	[15]

Supplementary Table S7: Techno-economic assumptions for open cycle gas power plants

Gas power plant (OCGT)	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency (%)	0.4	0.4	0.4	0.4	0.43	0.43	0.44	0.44	0.45	[15]
Availability Factor	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	[15]
Investment Cost (k€/MW)	574	574	574	574	574	574	574	574	574	[15]
O&M Cost (k€/MW)	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.2	[15]
Variable Cost (ex. Fuel) (k€/GWh)	11.5	11.5	11.5	11.5	11.5	11.5	11.5	11.5	11.5	[15]
Technical Lifetime (years)	30	30	30	30	30	30	30	30	30	[15]

Supplementary Table S8: Techno-economic assumptions for nuclear power plants

Nuclear power plants	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency (%)	0.37	0.37	0.37	0.37	0.38	0.38	0.38	0.38	0.38	[15]
Availability Factor	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	[15]
Investment Cost (k€/MW)	4930	4694	4537	4407	4276	4120	3963	3937	3911	[15]
O&M Cost (k€/MW)	108	103	99	97	94	90	87	86	86	[16]
Variable Cost (ex. Fuel) (k€/GWh)	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	[16]
Fuel cost (k€/GWh)	2.0	2.3	2.7	3.1	3.9	4.7	5.5	6.6	7.8	[15]
Technical Lifetime (years)	60	60	60	60	60	60	60	60	60	[16]

3.1.2. Combined heat & power

The tables below show the technological parameters and costs assumed for fossil-based combined heat and power (CHP) plants. The ratio between heat and electricity generation is reflected in the "heat to power ratio", whereas the coefficient of electricity to heat (CEH) is a parameter that defines the slope on the iso-fuel line between full condensing mode and full CHP mode [17].

Supplementary Table S9: Techno-economic assumptions for gas-fired CHP plants

CCGT CHP	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Electrical Efficiency	0.45	0.45	0.46	0.46	0.47	0.47	0.48	0.48	0.49	[15]
Availability Factor	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	[15]
Heat to Power Ratio	1.0	1.0	1.0	1.0	0.9	0.9	0.9	0.9	0.9	[15]
Coefficient of Electricity to Heat	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	-
Investment Cost (k€/MW)	1053	1053	1043	1038	1033	1028	1022	1017	1012	[15]
Fixed O&M Costs (k€/MW)	42.8	42.8	42.4	42.2	42.0	41.8	41.6	41.4	41.2	[15]
Variable Cost (ex. Fuel) (k€/GWh)	4.2	4.2	4.2	4.2	4.2	4.2	4.2	4.2	4.2	[15]
Technical Lifetime (years)	30	30	30	30	30	30	30	30	30	[15]

Supplementary Table S10: Techno-economic assumptions for coal-fired CHP plants

Coal CHP	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency (%)	0.39	0.39	0.41	0.41	0.42	0.42	0.43	0.43	0.43	[15]
Availability Factor	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	[15]
Heat to Power Ratio	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	[15]
Coefficient of Electricity to Heat	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	-
Investment Cost (k€/MW)	2117	2117	2117	2117	2117	2117	2117	2117	2117	[15]
Fixed O&M Costs (k€/MW)	42	42	42	42	42	42	42	42	42	[15]
Variable Cost (ex. Fuel) (k€/GWh)	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3	[15]
Technical Lifetime (years)	35	35	35	35	35	35	35	35	35	[15]

Supplementary Table S11: Techno-economic assumptions for waste-fired CHP plants

Waste CHP	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency (%)	0.27	0.27	0.31	0.31	0.34	0.34	0.37	0.37	0.42	[15]
Availability Factor	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	[15]
Heat to Power Ratio	2.3	2.3	1.9	1.9	1.6	1.6	1.4	1.4	1.1	[15]
Coefficient of Electricity to Heat	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	-
Investment Cost (k€/MW)	6341	6341	5872	5669	5465	5272	5079	4907	4735	[15]
Fixed O&M Costs (k€/MW)	198	198	184	177	171	165	159	154	148	[15]
Variable Cost (ex. Fuel) (k€/GWh)	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	[15]
Technical Lifetime (years)	25	25	25	25	25	25	25	25	25	[15]

3.1.3. Fossil heat generation

Supplementary Table S12: Techno-economic assumptions for natural gas boilers

Natural Gas Boiler	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	[18]
Availability Factor	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	[18]
Investment Cost (k€/MW)	134	134	134	134	134	134	134	134	134	[18]
Fixed O&M Costs (k€/MW)	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	[18]
Variable costs (ex. Fuel) (k€/GWh)	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	[18]
Technical Lifetime	20	20	20	20	20	20	20	20	20	[18]

Supplementary Table S13: Techno-economic assumptions for oil boilers

Oil Boiler	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency (%)	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	[18]
Availability Factor	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	[18]
Investment Cost (k€/MW)	96.2	96.2	96.2	96.2	96.2	96.2	96.2	96.2	96.2	[18]
Fixed O&M Costs (k€/MW)	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	[18]
Variable costs (ex. Fuel) (k€/GWh)	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	[18]
Technical Lifetime	20	20	20	20	20	20	20	20	20	[18]

Supplementary Table S14: Techno-economic assumptions for waste boilers

Waste Boiler	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency (%)	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	[18]
Availability Factor	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	[18]
Investment Cost (k€/MW)	2855	2620	2593	2567	2541	2515	2515	2515	2515	[18]
Fixed O&M Costs (k€/MW)	92.8	92.8	92.8	92.8	92.8	92.8	92.8	92.8	92.8	[18]
Variable costs (ex. Fuel) (k€/GWh)	8.7	8.7	8.7	8.7	8.7	8.7	8.7	8.7	8.7	[18]
Technical Lifetime	20	20	20	20	20	20	20	20	20	[18]

3.2. Renewable Energy Resources

The tables below show the technological parameters and costs assumed for renewable energy resources.

The investment cost for solar PV, onshore- and offshore wind have been split into three cost classes, respectively a low, medium and high cost class. These cost classes are introduced to reflect that various locations are available for installations of renewable technologies, with associated varying costs. For example for offshore wind, the water depth plays an important part in the cost of the installations. Near-shore offshore wind turbines, often bottom-fixed, are cheaper than floating wind turbines far offshore. This is also reflected in the maximum technical potential of each of these renewable resources, which for simplicity is split evenly amongst the three cost classes.

3.2.1. Renewable Electricity Generation

Supplementary Table S15: Techno-economic assumptions for onshore wind – low cost class

Onshore wind - low	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	1090	1090	1040	1010	980	960	940	930	920	[19]
O&M Cost (k€/kWh)	32.7	32.7	31.2	30.3	29.4	28.8	28.2	27.9	27.6	[19]
Technical Lifetime (years)	20	20	22	22	25	25	25	25	25	[15]

Supplementary Table S16: Techno-economic assumptions for onshore wind – medium cost class

Onshore wind - medium	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	1350	1350	1290	1250	1210	1190	1170	1150	1130	[19]
O&M Cost (k€/kWh)	40.5	40.5	38.7	37.5	36.3	35.7	35.1	34.5	33.9	[19]
Technical Lifetime (years)	20	20	22	22	25	25	25	25	25	[15]

Supplementary Table S17: Techno-economic assumptions for onshore wind – high cost class

Onshore wind - high	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	1850	1850	1760	170	1660	1630	1600	1580	1560	[19]
O&M Cost (k€/kWh)	55.5	55.5	52.8	51.1	49.8	48.9	48	47.4	46.8	[19]
Technical Lifetime (years)	20	20	22	22	25	25	25	25	25	[15]

Supplementary Table S18: Techno-economic assumptions for offshore wind – low cost class

Offshore wind - low	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	3500	3500	2870	2720	2570	2500	2430	2380	2330	[19]
O&M Cost (k€/kWh)	70	70	57.4	54.4	51.4	50	48.6	47.6	46.6	[19]
Technical Lifetime (years)	20	20	25	25	30	30	30	30	30	[15]

Supplementary Table S19: Techno-economic assumptions for offshore wind – medium cost class

Offshore wind - medium	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	3600	3600	2950	2800	2650	2570	2490	2440	2390	[19]
O&M Cost (k€/kWh)	72	72	59	56	53	51.4	49.8	48.8	47.8	[19]
Technical Lifetime (years)	20	20	25	25	30	30	30	30	30	[15]

Supplementary Table S20: Techno-economic assumptions for offshore wind – high cost class

Offshore wind - high	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	5500	5500	4510	4275	4040	3925	3810	3735	3660	[19]
O&M Cost (k€/kWh)	110	110	90.2	85.5	80.8	78.5	76.2	74.7	73.2	[19]
Technical Lifetime (years)	20	20	25	25	30	30	30	30	30	[15]

Supplementary Table S21: Techno-economic assumptions for solar PV – low cost class

Solar PV - low	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	1600	1020	790	695	600	525	450	410	370	[19]
O&M Cost (k€/kWh)	27.2	17.34	13.43	11.815	10.2	8.925	7.65	6.97	6.29	[19]

Technical Lifetime (years)	25	25	25	25	25	25	25	25	25	[15]

Supplementary Table S22: Techno-economic assumptions for solar PV – medium cost class

Solar PV - medium	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	1734	1140	880	775	670	590	510	460	410	[19]
O&M Cost (k€/kWh)	29.5	19.4	15.0	13.2	11.4	10.0	8.7	7.8	7.0	[19]
Technical Lifetime (years)	25	25	25	25	25	25	25	25	25	[15]

Supplementary Table S23: Techno-economic assumptions for solar PV – high cost class

Solar PV - high	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	1960	1360	1050	925	800	700	600	545	490	[19]
O&M Cost (k€/kWh)	33.3	23.1	17.9	15.7	13.6	11.9	10.2	9.3	8.3	[19]
Technical Lifetime (years)	25	25	25	25	25	25	25	25	25	[15]

The cost of hydropower is difficult to determine, as estimates from the literature vary considerably. Investment costs depend largely on the size of the project, with costs ranging from as low as 770 €$_{2015}$/kW to about 7960 €$_{2015}$/kW [18,20–23]. Therefore, the cost of hydropower is split into three cost classes for hydropower plants with reservoirs, and one cost class for run-of-river hydropower.

Supplementary Table S24: Techno-economic assumptions for hydropower with reservoir (low cost class)

Hydropower – low	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	1740	1740	1740	1740	1730	1730	1730	1730	1730	[19]
O&M Cost (k€/MW)	17	17	17	17	17	17	17	17	17	[19]
Technical Lifetime (years)	60	60	60	60	60	60	60	60	60	[15]

Supplementary Table S25: Techno-economic assumptions for hydropower with reservoir (medium cost class)

Hydropower – medium	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	3500	3500	3500	3498	3490	3485	3480	3475	3470	[19]
O&M Cost (k€/kWh)	18	18	18	17	17	17	17	17	17	[19]
Technical Lifetime (years)	60	60	60	60	60	60	60	60	60	[15]

Supplementary Table S26: Techno-economic assumptions for hydropower with reservoir (high cost class)

Hydropower - high	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	5000	5000	5000	4985	4980	4975	4970	4965	4960	[19]
O&M Cost (k€/kWh)	25	25	25	25	25	25	25	25	25	[19]
Technical Lifetime (years)	60	60	60	60	60	60	60	60	60	[15]

Supplementary Table S27:Techno-economic assumptions for run-of-river hydropower

Hydropower (Run-of-river)	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	3000	3000	3000	2995	2990	2985	2980	2975	2970	[19]
O&M Cost (k€/kWh)	15	15	15	15	15	15	15	15	15	[19]

Technical Lifetime (years)	60	60	60	60	60	60	60	60	60	[15]

Supplementary Table S28: Techno-economic assumptions for concentrated solar power (CSP)

Concentrated Solar Power	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	5670	5280	4070	3690	3310	3160	3010	2945	2880	[19]
O&M Cost (k€/kWh)	96	90	69	46	56	14	51	14	49	[19]
Technical Lifetime (years)	30	30	30	30	30	30	30	30	30	[19]

Supplementary Table S29: Techno-economic assumptions for biomass power plants

Biomass Power Plant	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency (%)	0.34	0.34	0.35	0.35	0.36	0.37	0.38	0.38	0.38	[15]
Availability Factor (hours)	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	[15]
Investment Cost (k€/MW)	3014	3014	2733	2603	2472	2357	2242	2138	2034	[15]
O&M Cost (k€/MW)	66	66	60	57	54	52	49	47	45	[15]
Variable Cost (ex. Fuel) (€/kWh)	3.7	3.7	3.7	3.7	3.7	3.7	3.7	3.7	3.7	[15]
Technical Lifetime (years)	25	25	25	25	25	25	25	25	25	[15]

Supplementary Table S30: Techno-economic assumptions for biomass-fired CHP plants

Biomass CHP	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency (%)	30	30	30	30	30	30	30	30	30	[15]
Availability Factor	0.64	0.65	0.675	0.675	0.675	0.675	0.725	0.725	0.725	[15]
Heat to Power Ratio	2	2	2	2	2	2	2	2	2	[15]
Coefficient of Electricity to Heat	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	-
Investment Cost (k€/MW)	3600	3600	3330	3255	3180	3115	3050	2980	2910	[19]
Fixed O&M Costs (k€/MW)	72	72	66.6	65.1	63.6	62.3	61	59.6	58.2	[19]
Variable costs (ex. Fuel) (k€/GWh)	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	[15]
Technical Lifetime (years)	25	25	25	25	25	25	25	25	25	[15]

Supplementary Table S31: Techno-economic assumptions for geothermal hydrothermal

Geothermal hydrothermal	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	3540	3540	3350	3250	3150	3085	3020	2965	2910	[19]
O&M Cost (k€/kWh)	71	71	67	65	63	62	60	59	58	[19]
Technical Lifetime (years)	30	30	30	30	30	30	30	30	30	[15]
Availability Factor	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	[15]

Supplementary Table S32: Techno-economic assumptions for enhanced geothermal systems (EGS)

Geothermal EGS	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	11790	11790	11420	11130	10840	10690	10540	10370	10200	[19]
O&M Cost (k€/kWh)	236	236	228	223	217	214	211	207	204	[19]
Technical Lifetime (years)	30	30	30	30	30	30	30	30	30	[15]
Availability Factor	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	[15]

Supplementary Table S33: Techno-economic assumptions for wave power

Wave Power	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref

Investment Cost (k€/MW)	7910	7910	6310	5815	5320	4680	4040	3640	3240	[19]
O&M Cost (k€/kWh)	316	316	252	233	213	187	162	146	130	[19]
Technical Lifetime (years)	20	20	20	20	20	20	20	20	20	[15]
Availability Factor (%)	0.2	0.2	0.23	0.26	0.28	0.3	0.32	0.34	0.36	[15]

Supplementary Table S 34: Techno-economic assumptions for tidal power

Tidal Power	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	6160	6160	4920	4530	4140	3645	3150	2835	2520	[19]
O&M Cost (k€/kWh)	400	400	320	294	269	237	205	184	164	[19]
Technical Lifetime (years)	20	20	20	20	20	20	20	20	20	[15]
Availability Factor (%)	0.34	0.34	0.37	0.39	0.4	0.41	0.42	0.44	0.45	[15]

3.2.2. Renewable Heat Generation

Supplementary Table S35: Techno-economic assumptions for geothermal heat pumps

Geothermal heat pump	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Seasonal Performance Factor (SPF)	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	[18]
Availability Factor	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	[18]
Investment Cost (k€/MW)	1382	1268	1205	1141	1078	1015	1322	1322	1322	[18]
Fixed O&M Costs (k€/MW)	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	[18]
Variable costs (ex. Fuel) (k€/GWh)	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	[18]
Technical Lifetime	20	20	20	20	20	20	20	20	20	[18]

Supplementary Table S36: Techno-economic assumptions for solar thermal collectors

Solar thermal collector	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Investment Cost (k€/MW)	322.3	295.7	256	216	176	136.0	136.0	136.0	136.0	[18]
Fixed O&M Costs (k€/MW)	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	[18]
Technical Lifetime	25	25	25	25	25	25	25	25	25	[18]

Supplementary Table S37: Techno-economic assumptions for biomass boilers

Biomass boiler	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency (%)	90	90	90	90	90	90	90	90	90	[18]
Availability Factor	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	[18]
Investment Cost (k€/MW)	728.2	668.1	664.8	661.4	658.1	654.8	697.6	697.6	697.6	[18]
Fixed O&M Costs (k€/MW)	30.1	30.1	30.1	30.1	30.1	30.1	30.1	30.1	30.1	[18]
Variable costs (ex. Fuel) (k€/GWh)	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	[18]
Technical Lifetime	15	15	15	15	15	15	15	15	15	[18]

Supplementary Table S38: Techno-economic assumptions for electric boilers

Electric Boiler	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency (%)	98	98	98	98	98	98	98	98	98	[18]
Availability Factor (-)	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	[18]
Investment Cost (k€/MW)	81.8	81.8	81.8	81.8	81.8	81.8	81.8	81.8	81.8	[18]

Fixed O&M Costs (k€/MW)	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	[18]
Technical Lifetime (years)	20	20	20	20	20	20	20	20	20	[18]

Supplementary Table S39: Techno-economic assumptions for electric heat pumps

Electric Heat Pump	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Seasonal Performance Factor (SPF)	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	[18]
Availability Factor (-)	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	[18]
Investment Cost (k€/MW)	1027	942	895	848	801	753	753	753	753	[18]
Fixed O&M Costs (k€/MW)	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	[18]
Variable costs (ex. Fuel) (k€/GWh)	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6	[18]
Technical Lifetime	15	15	15	15	15	15	15	15	15	[18]

3.2.3. Renewables maximum potential

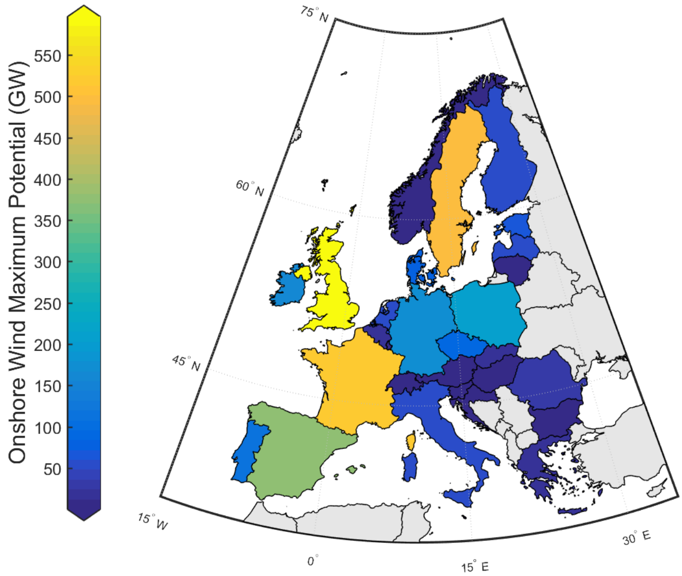
Maximum theoretical capacities for renewable energy technologies are used as an input to TIMES-Europe in order to limit the maximum installed capacities of a certain technology in a given country based on technical, environmental or political constraints.

Maximum installed onshore wind capacity (see Supplementary Figure S11 and Supplementary Table S40) is based on estimates of available land area for onshore wind installations in each country, taking into account protected areas, mountainous areas etc. [24–26]. The available installed capacity is further found by multiplying the available land area with a power density of 3 MW/km^2. The maximum potential of electricity generation is estimated by using the average capacity factor from Renewables.ninja and the available maximum installed capacity.

Offshore wind is estimated in a similar matter. We have used available offshore area for wind energy farms within national jurisdictions, multiplied by a higher capacity density of 15 MW/km^2 (reflecting that turbines are generally bigger offshore) [27,28].

Solar PV combines both utility scale and rooftop PV, and is based on [29]. Solar CSP with storage is assumed only available in countries with high solar irradiation, respectively Spain (158 GW), Portugal (22 GW), Italy (16 GW), Greece (5 GW) and Malta (0.4 GW) [30]. Pfenninger et al. [31] found that with current thermal storage technology, solar CSP can act as a dispatchable or base-load capable technology in parts of the world, and is therefore treated as such in TIMES-Europe. The capacity factor of all CSP plants is assumed to be 41 %, modelled after the existing Andasol power plant in Spain [32]. This is a rather conservative estimate, e.g. [30] uses a 55 % capacity factor.

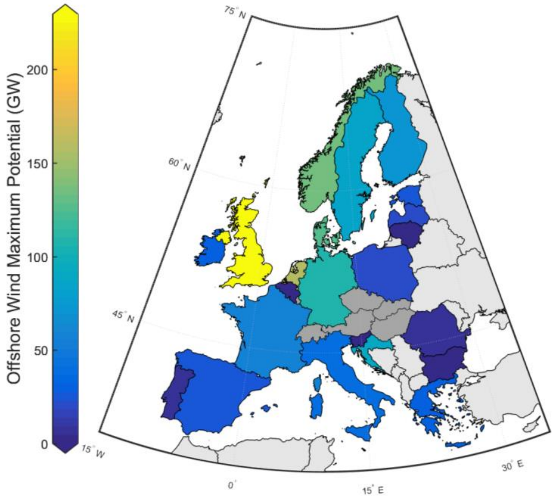
New regulated hydropower is based on [33], whereas small run-of-the-river hydro is based on [34]. The use of biomass and waste is based on [35–38], using scenarios with a “sustainable theoretical potential for biomass”. Geothermal electricity generation is split into two cost classes, representing hydrothermal resources and enhanced geothermal systems (EGS). Their maximum theoretical potentials are based on [39], where the potential in 2030 is allocated to hydrothermal systems while the potential in 2050 is EGS (GEOELEC assumes that EGS is economically competitive in 2050, thus becoming widely available and therefore drastically increasing the potential). Estimates of the theoretical potential for tidal and wave is estimated based on the coastline length of each country [40] through the procedures proposed by Jacobson et al. and Gunn & Stock-Williams [29][41]. The potential for new pumped hydro storage (PHS) plants is based on [42]. Here we use the T1 scenario, in which two reservoirs already exists with sufficient height difference and with a distance of maximum 5 kilometers.



Supplementary Figure S11: Onshore wind maximum installed capacity (GW)

Supplementary Table S40: Onshore wind maximum potential capacity and generation

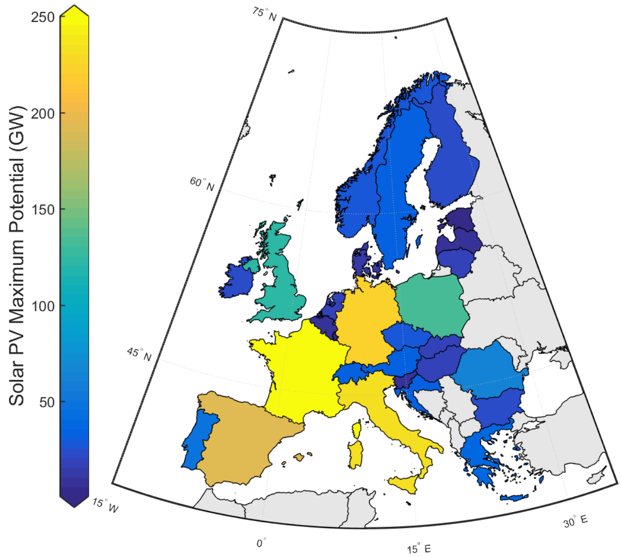
Onshore Wind							
Max. Theoretical Potential (GW)				Max. Generation Potential (TWh)			
AT	12	IT	49	AT	27.9	IT	84
BE	14	LT	2	BE	29.9	LT	3.8
BG	8.8	LU	2	BG	17.8	LU	4.2
CH	1	LV	51	CH	1.7	LV	112
CZ	87	MT	0.1	CZ	170	MT	0.24
DE	182	NL	56	DE	308	NL	120.3
DK	85	NO	7	DK	193	NO	17.4
EE	66	PL	218	EE	141.4	PL	470.6
ES	383	PT	122	ES	895	PT	288
FI	52	RO	25	FI	145	RO	54
FR	528	SE	510	FR	1139	SE	1131
GR	21	SI	1	GR	49	SI	0.5
HR	2	SK	13	HR	2.3	SK	17
HU	4	UK	596	HU	8.92	UK	1530
IE	167			IE	432		



Supplementary Figure S12: Offshore wind maximum installed capacity (GW)

Supplementary Table S41: Offshore wind maximum installed capacity and generation potential

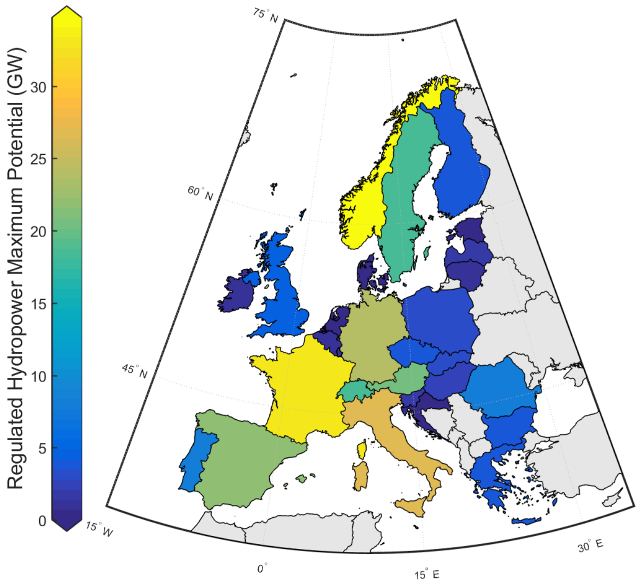
Offshore Wind							
Max. Theoretical Potential (GW)				Max Generation Potential (TWh)			
AT	0	IT	38	AT	0	IT	64
BE	3	LT	4	BE	9.2	LT	11
BG	3	LU	0	BG	0	LU	0
CH	0	LV	19	CH	0	LV	0
CZ	0	MT	0.2	CZ	0	MT	0.4
DE	110	NL	161	DE	319	NL	465
DK	130	NO	140	DK	403	NO	637
EE	25	PL	21	EE	67	PL	56
ES	23	PT	8	ES	82	PT	31
FI	74	RO	9	FI	232	RO	0
FR	60	SE	84	FR	242	SE	345
GR	32	SI	0.1	GR	116	SI	0
HR	91	SK	0	HR	150	SK	0
HU	0	UK	230	HU	0	UK	772
IE	32			IE	89		



Supplementary Figure S13: Solar PV maximum installed capacity (GW)

Supplementary Table S42: Solar PV maximum installed capacity and generation potential

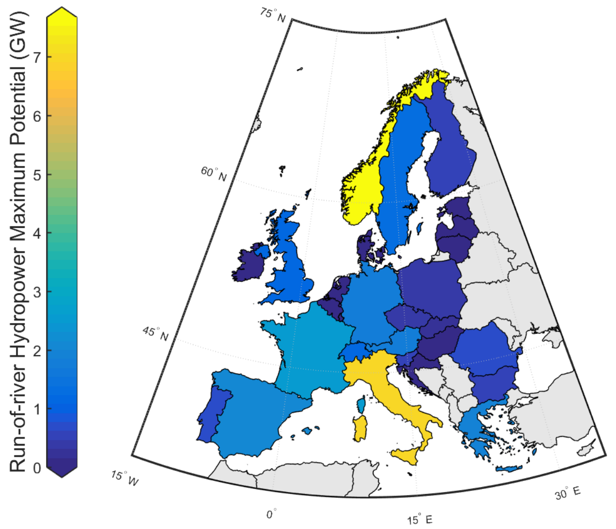
Solar PV							
Max. Theoretical Potential (GW)				**Max Generation Potential (TWh)**			
AT	35	**IT**	238	**AT**	42	**IT**	323
BE	10	**LT**	16	**BE**	11	**LT**	16
BG	26	**LU**	1	**BG**	34	**LU**	0.9
CH	35	**LV**	8	**CH**	48	**LV**	8
CZ	29	**MT**	1	**CZ**	33	**MT**	1
DE	228	**NL**	18	**DE**	248	**NL**	19
DK	15	**NO**	30	**DK**	15	**NO**	26
EE	4	**PL**	134	**EE**	3.9	**PL**	141
ES	197	**PT**	50	**ES**	289	**PT**	73
FI	25	**RO**	63	**FI**	21	**RO**	78
FR	250	**SE**	36	**FR**	306	**SE**	31
GR	38	**SI**	9	**GR**	54	**SI**	11
HR	19	**SK**	20	**HR**	23	**SK**	23
HU	34	**UK**	127	**HU**	41	**UK**	119
IE	25			**IE**	23		



Supplementary Figure S14: Regulated hydropower maximum installed capacity (GW)

Supplementary Table S43: Regulated hydropower maximum installed capacity and generation potential

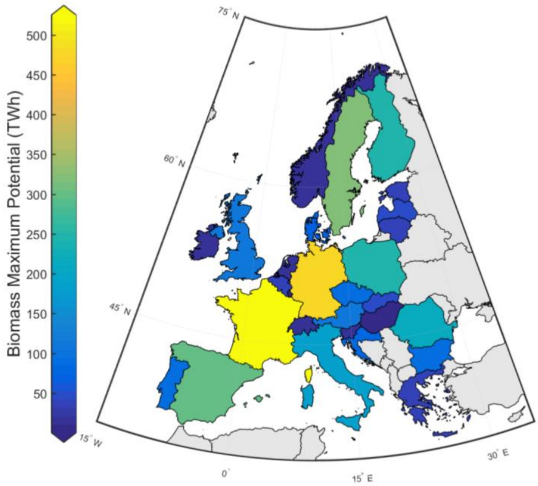
Regulated Hydropower							
Max. Theoretical Potential (GW)				Max Generation Potential (TWh)			
AT	21	IT	27.2	AT	82.5	IT	53.8
BE	1.4	LT	1.106	BE	3.2	LT	4.3
BG	3.7	LU	1.347	BG	8	LU	3.5
CH	19	LV	1.733	CH	74.5	LV	3.5
CZ	3.7	MT	0	CZ	6.7	MT	0
DE	24	NL	0.037	DE	126	NL	0.1
DK	0	NO	34.7	DK	0	NO	154
EE	0.03	PL	3.4	EE	0.13	PL	4.2
ES	22.2	PT	8.2	ES	42.6	PT	18
FI	3.8	RO	7.8	FI	18.3	RO	21.6
FR	33.7	SE	18.8	FR	99.6	SE	61
GR	3.9	SI	1.5	GR	11.7	SI	6.3
HR	2.6	SK	3.1	HR	9.7	SK	9.4
HU	0.06	UK	4.7	HU	0.2	UK	16
IE	0.7			IE	2.3		



Supplementary Figure S15: ROR hydropower maximum installed capacity (GW)

Supplementary Table S44: Run-of-river maximum installed capacity and generation potential

Run-of-river Hydropower							
Max. Theoretical Potential (GW)				**Max Generation Potential (TWh)**			
AT	1.8	**IT**	7.1	**AT**	6.9	**IT**	26.5
BE	0.1	**LT**	0.04	**BE**	0.3	**LT**	0.2
BG	0.6	**LU**	0.04	**BG**	1.8	**LU**	0.1
CH	1.2	**LV**	0.08	**CH**	3.7	**LV**	0.2
CZ	0.5	**MT**	0	**CZ**	2.1	**MT**	0
DE	1.8	**NL**	0.01	**DE**	8.0	**NL**	0.03
DK	0.01	**NO**	7.7	**DK**	0.04	**NO**	33.9
EE	0.01	**PL**	0.3	**EE**	0.04	**PL**	1.4
ES	2.2	**PT**	0.8	**ES**	6.5	**PT**	2.0
FI	0.6	**RO**	0.7	**FI**	2.3	**RO**	2.7
FR	2.6	**SE**	1.3	**FR**	8.9	**SE**	5.7
GR	2.0	**SI**	0.5	**GR**	2.0	**SI**	1.1
HR	0.100	**SK**	0.2	**HR**	0.3	**SK**	0.9
HU	0.03	**UK**	1.2	**HU**	0.1	**UK**	1.7
IE	0.06			**IE**	0.2		

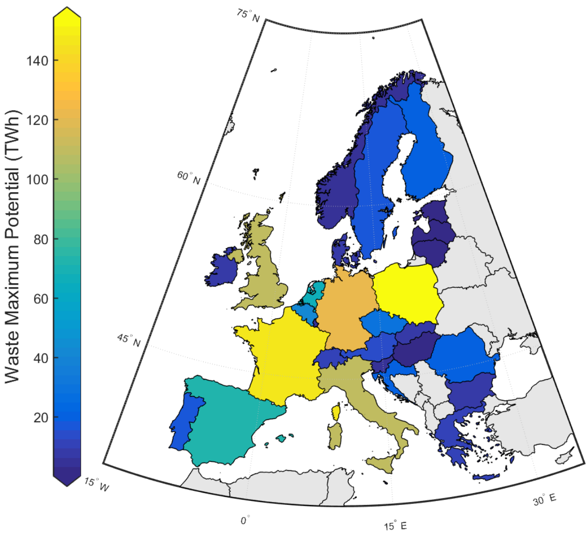


Supplementary Figure S16: Biomass generation potential (TWh)

Supplementary Table S45: Biomass generation potential (TWh)

Biomass			
Max Generation Potential (TWh)			
AT	109	**IT**	183
BE[2]	37	**LT**	42
BG	89	**LU**	3
CH	13	**LV**	46
CZ	93	**MT**[3]	0.2
DE	491	**NL**	14
DK	66	**NO**	17
EE	36	**PL**	253
ES	306	**PT**	95
FI	257	**RO**	219
FR	525	**SE**	322
GR	43	**SI**	20
HR	4	**SK**	46
HU	80	**UK**	116
IE	15		

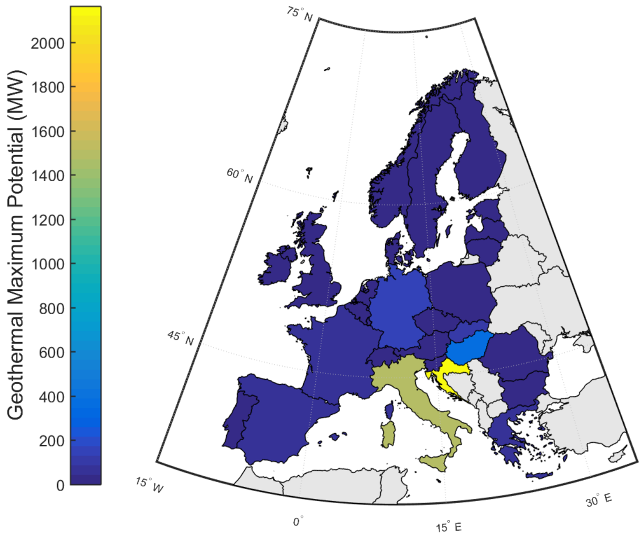
[2] Belgium and Luxembourg were aggregated, and is separated by their respective share of land area
[3] Numbers for Malta not available. Used area weighted number based on Italy.



Supplementary Figure S17: Waste generation potential (TWh)

Supplementary Table S46: Waste generation potential

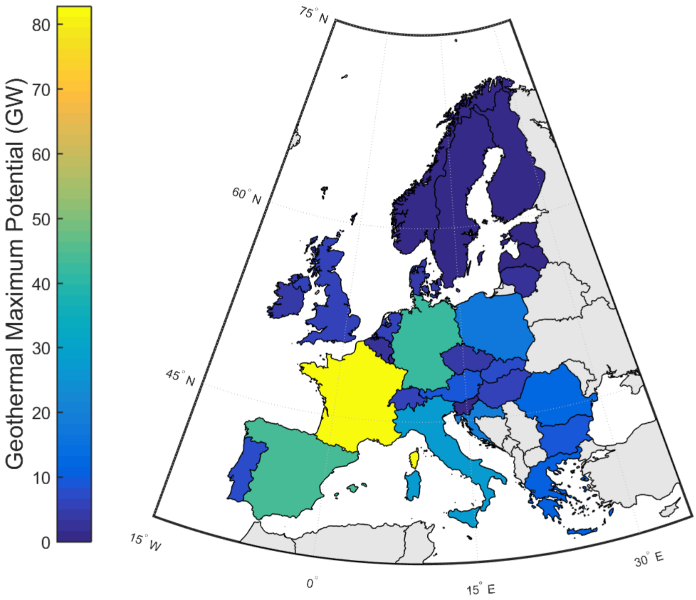
Waste			
Max Generation Potential (TWh)			
AT	13	IT	112
BE	41	LT	3
BG	7	LU	3
CH	10	LV	0.7
CZ	31	MT	0.1
DE	124	NL	68
DK	6	NO	5
EE	1	PL	154
ES	76	PT	18
FI	21	RO	20
FR	150	SE	16
GR	11	SI	3
HR	2	SK	9
HU	20	UK	111
IE	8		



Supplementary Figure S18: Geothermal hydrothermal maximum installed capacity (MW)

Supplementary Table S47: Geothermal hydrothermal maximum installed capacity and generation potential

Geothermal electricity (Hydrothermal)							
Max. Theoretical Potential (MW)				**Max Generation Potential (TWh)**			
AT	13	**IT**	1531	**AT**	0.1	**IT**	11.8
BE	0	**LT**	5	**BE**	0.0	**LT**	0.0
BG	12	**LU**	0	**BG**	0.1	**LU**	0.0
CH	0.2	**LV**	2	**CH**	0.0	**LV**	0.0
CZ	5	**MT**	0	**CZ**	0.0	**MT**	0.0
DE	173	**NL**	30	**DE**	1.3	**NL**	0.2
DK	4	**NO**	0	**DK**	0.0	**NO**	0.0
EE	5	**PL**	0	**EE**	0.0	**PL**	0.0
ES	66	**PT**	20	**ES**	0.5	**PT**	0.2
FI	0	**RO**	22	**FI**	0.0	**RO**	0.2
FR	49	**SE**	0	**FR**	0.4	**SE**	0.0
GR	60	**SI**	1	**GR**	0.5	**SI**	0.0
HR	381	**SK**	112	**HR**	2.9	**SK**	0.9
HU	2164	**UK**	3	**HU**	16.7	**UK**	0.0
IE	24			**IE**	0.2		



Supplementary Figure S19: Geothermal EGS maximum installed capacity (GW)

Supplementary Table S48: Geothermal EGS maximum installed capacity and generation potential

Geothermal electricity (EGS)							
Max. Theoretical Potential (GW)				**Max Generation Potential (TWh)**			
AT	8.5	**IT**	27.1	**AT**	67	**IT**	214
BE	2.8	**LT**	2.4	**BE**	22	**LT**	19
BG	9.1	**LU**	0.3	**BG**	72	**LU**	3
CH	5.4	**LV**	0.4	**CH**	43	**LV**	3
CZ	3.9	**MT**	0.0	**CZ**	31	**MT**	0
DE	43.7	**NL**	6.5	**DE**	344	**NL**	52
DK	3.7	**NO**	0.0	**DK**	29	**NO**	0
EE	0.2	**PL**	18.2	**EE**	2	**PL**	144
ES	44.1	**PT**	8.0	**ES**	348	**PT**	63
FI	0.0	**RO**	13.3	**FI**	0	**RO**	104
FR	82.8	**SE**	0.1	**FR**	653	**SE**	1
GR	10.3	**SI**	1.0	**GR**	81	**SI**	8
HR	6.0	**SK**	6.8	**HR**	47	**SK**	54
HU	19.9	**UK**	5.3	**HU**	157	**UK**	42
IE	3.4			**IE**	27		

3.4. Storage Technologies

Supplementary Table S49: Techno-economic assumptions for pumped hydro storage (PHS)

Pumped Hydro Storage	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Roundtrip efficiency (%)	0.8	0.8	0.82	0.84	0.85	0.87	0.88	0.89	0.9	[16]
Investment cost (k€/MWh)	70	70	70	70	70	70	70	70	70	[16]
Fix. O&M Cost (k€/MWh)	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	[16]
Lifetime (years)	60	60	60	60	60	60	60	60	60	[16]

Supplementary Table S50: Techno-economic assumptions for li-ion battery storage

Li-ion Batteries	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Roundtrip efficiency (%)	90	90	90	90	90	90	90	90	90	[16]
Investment cost (k€/MWh)	870	600	300	200	150	120	100	85	75	[16]
Fix. O&M Cost (k€/MWh)	43.5	24	9	5	3.75	3	2.5	2.13	1.88	[16]
Var. Costs (Stg) (k€/GWh)	2	2	2	2	2	2	2	2	2	[16]
Lifetime	15	15	15	15	15	15	15	15	15	[16]

Supplementary Table S51: Techno-economic assumptions for underground thermal energy storage (UTES)

UTES	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Roundtrip efficiency	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	[16]
Investment Cost (k€/MWh)	50	50	40	30	30	20	20	20	20	[16]
O&M Costs (Storage) (k€/MWh)	0.75	0.75	0.6	0.45	0.45	0.3	0.3	0.3	0.3	[16]
Lifetime	25	25	25	25	25	25	25	25	25	[16]

Supplementary Table S52: Techno-economic assumptions for adiabatic compressed air energy storage (a-CAES)

CAES	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Efficiency	0.54	0.59	0.65	0.7	0.7	0.7	0.7	0.7	0.7	[16]
Investment Cost (€/kWh)	35	35	35	33	31.1	30.5	29.8	28	26	[16]
O&M Costs (Storage) (€/GWh)	0.5	0.46	0.46	0.43	0.4	0.4	0.39	0.36	0.34	[16]
Var. Costs (Stg) (k€/GWh)	12	12	12	12	12	12	12	12	12	[16]
Lifetime	40	40	55	55	55	55	55	55	55	[16]

3.5. Hydrogen

Hydrogen is modelled with a full value chain, from hydrogen production through two types of electrolysers (steam methane reforming is not included), storage and finally fuel cells to convert the hydrogen back to electricity and heat.

Supplementary Table S53: Techno-economic assumptions for hydrogen storage

Hydrogen Storage (compressed)	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Lifetime (years)	20	20	20	20	20	20	20	20	20	[23]
Storage Efficiency (%)	90	90	90	90	90	90	90	90	90	[43]
Boil-off rate (%/year)	40	40	40	40	40	40	40	40	40	[44]
Investment Cost (€/kWh)	18.6	17.0	11.2	9.7	8.2	6.7	5.3	3.8	2.3	[23]

O&M Costs (€/kWh)	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	[23]

Supplementary Table S54: Techno-economic assumptions for alkaline hydrogen electrolysers

Hydrogen Electrolyser (Alkaline)	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Lifetime (Years)	10	10	10	10	10	10	10	10	10	[45]
Efficiency (%)	63	63	64	65	66	67	68	69	70	[45]
Availability Factor (%)	98	98	98	98	98	98	98	98	98	[45]
Investment Cost (k€/MW)	1954	1793	1214	1176	1118	1060	1060	1060	1060	[45]
O&M Costs (k€/MW)	36	33	30	28	26	26	26	26	26	[45]

Supplementary Table S55: Techno-economic assumptions for hydrogen PEM electrolysers

Hydrogen Electrolyser (PEM)	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Lifetime (Years)	8	8	9	9	9	9	9	9	9	[45]
Efficiency (%)	63	63	68	69	71	71	71	71	71	[45]
Availability Factor (%)	98	98	98	98	98	98	98	98	98	[45]
Investment Cost (kNOK/MW)	3298	3026	1927	1677	1291	1291	1291	1291	1291	[45]
O&M Costs (kNOK/MW)	36	33	30	28	26	26	26	26	26	[45]

Supplementary Table S56:Techno-economic assumptions for PEM fuel cells

Hydrogen Fuel Cell	2010	2015	2020	2025	2030	2035	2040	2045	2050	Ref
Lifetime (years)	7	7	8	8	9	9	9	9	9	[46,47]
Electrical Efficiency (%)	0.35	0.35	0.4	0.425	0.45	0.45	0.45	0.45	0.45	[46,47]
Availability Factor (%)	97	97	97	97	97	97	97	97	97	[46,47]
Heat to power ratio (-)	1.57	1.57	1.25	1.12	1.00	1.00	1.00	1.00	1.00	[46,47]
Investment Cost (k€/MW)	3488	3200	2410	1620	830	830	830	830	830	[46,47]
O&M Costs (k€/MW)	174	160	121	81	42	42	42	42	42	[46,47]

3.6. Grid Expansions

TIMES-Europe allows for endogenous investments in additional grid expansions from 2020. The specific cost of these expansions are estimated by following a generic methodology presented in [48,49]. The cost per MW of each interconnection is calculated based on the length between the two countries being connected, where the length is calculated from the two countries' geographical centres. The assumed investment cost for underground and submarine HVDC cables are 1123 €/km/MW and 1276 €/km/MW respectively, with an additional 0.2 M€/MW for converter substations [49].

All future interconnections are assumed to be submarine or underground high-voltage direct current (HVDC) cables. HVDC cables offers a more expensive option compared to conventional overhead high-voltage alternating current (HVAC) lines, but avoids potential local opposition seen against overhead power lines [50].

In accordance with [48,49], a maximum length of 300 km is set for onshore interconnections. This procedure generally overestimates the length, and thus the cost, of each interconnection, which would become unrealistically high in cases where larger neighbouring countries (e.g. France and Germany) are connected. On the other hand, the general overestimation of the cost will compensate for the lack of considering local grid reinforcements.

3.6.1. Current grid

Interconnection capacities for 2015 are shown in Table 1. In this work, the net transfer capacity (NTC) between regions are used as interconnection capacities in the model. These are primarily based on data from ENTSO-E [51], and is supplemented with a number of other resources [52–59].

Table 1: NTC matrix for the countries included in the model, based primarily on [51] and supplemented by [52–59].

2015 Net Transfer Capacities (MW)																												
From / To	AT	BE	BG	HR	CZ	DK	EE	FI	FR	DE	GR	HU	IE	IT	LV	LT	LU	MT	NL	NO	PL	PT	RO	SK	SI	ES	SE	CH	UK
AT					1000					2200		800		285											900			1200	
BE									3400										2400										
BG											500												600						
HR												1200													1000				
CZ	600									800											1800			1200					
DK										1550										950							1980		
EE								350							850														
FI							350																				2050		
FR		2300								3200				995												500		1100	2000
DE	2000				2300	2085			2700								[4]		3000		1100						610	3500	
GR			550											500															
HU	800			800																			700	1300					
IE																													450
IT	220								2575		500														580			4165	
LV							750									1500													
LT															1300														
LU		700*								980																			
MT																													
NL		2400								3850										700									1000
NO						950													700								3895		
PL					800					1200														500			600		
PT																										1700			

[4] No real limit

RO			600									700																	
SK					2200							600									0								
SI	900			1000										160															
ES									1300													1500							
SE						2440		1650		600										3595									
CH	470								3200	1500				1810															
UK									2000				80						1000										
Import capacities from countries outside of study region																													
AL											150																		
BA				600																									
BY																1350													
MK			400								400																		
MA																										900			
ME																													
RU							1000								500	680													
RS			450	350								600											700						
TR																													
UA												650											200	400					

4. The Current European System

The base year of 2015 has been calibrated to the current real system. National generation capacities and electricity generation for 2015 is primarily based on ENTSO-E [5].

Small hydropower is defined as installations smaller than 10 MW. This is to use the “World Small Hydropower Development Report 2016” for installed capacities of small hydro as well as future technical potential [34]. The storage size and installed capacity of existing pumped hydro storage (PHS) plants are reported for 2015 [42,60], but their operation during those years are determined endogenously by the model.

CHP capacities is calibrated for 2010 using the Eurelectric’s Power Statistics and Trends 2013 [61], and then used to adjust the capacities for 2015. This report gives installed capacity of CHP in 2010 by fuel. However, in some cases, this capacity does not match the total capacity reported in the EU Reference Case 2016 (The EU 2016 gives the total capacity of cogeneration units, but it does not distinguish the type of fuel). In the cases where the EU Reference Case and the Eurelectric data does not match, the Eurelectric data is used to define the share (in %) of each fuel of the total capacity, and this share is then allocated to the total cogeneration capacity reported in the EU Reference Scenario. For example: For Bulgaria, according to the EU Reference Scenario, the total cogeneration capacity in 2010 is 1017 MW. In the Eurelectric report the total generation capacity is 723 MW, split into 120 MW coal, 290 MW oil, and 366 MW natural gas. This gives us shares of 15.4 % coal, 37.4 % oil, and 47.2 % natural gas respectively. Multiplying these shares with the total installed capacity from the EU Reference Scenario yields; 158 MW coal, 380 MW oil, and 478 MW natural gas. These capacities are then used as the current installed capacities for CHP-plants, and this capacity is also subtracted from the conventional fossil fuel capacity reported in the EU Reference Scenario. Subsequently, these shares are used to calibrate the installed capacities in 2015.

Data on district heat is based on the Euroheat & Power District Heat and Cooling Country by Country 2015 survey [62]. This report is used to estimate the installed capacities of heat generation technologies (boilers, heat pumps etc.). This data also includes heat generation from CHP, which is used to estimate the power to heat ratios of CHP, and thus the generation of electricity and heat from those plants. For the rest of the model horizon, this is determined endogenously by the model.

All numbers in the following tables are rounded to one decimal. In the cases where 0.0 is displayed the number is less than 0.1, but not zero.

4.1. Installed capacity

Supplementary Table S57: Installed capacity in 2015 in MW (AT-FI)

	AT	BE	BG	CH	CZ	DE	DK	EE	ES	FI
Nuclear	0	5927	2000	3333	4040	12227	0	0	7572	2752
Hydropower (REG)	8816	1353	1566	11586	753	3633	0	0	17168	2905
Hydropower (ROR)	1368	72	291	859	334	1826	10	8	2104	314
PHS[5]	3365 (125)	1308 (8)	864 (2)	1817 (369)	1147 (7)	6777 (39)	0	0	5260 (1530)	0
Onshore Wind	2258	1488	701	60	270	37757	3574	307	22740	898
Offshore wind	0	712	0	0	0	993	1271	0	0	5
Solar PV	587	2953	1041	756	2050	37446	601	1	6967	7
Solar CSP	0	0	0	0	0	0	0	0	0	0
Wave	0	0	0	0	0	0	0	0	0	0
Tidal	0	0	0	0	0	0	0	0	0	0
Biomass	0	872	64	0	0	977	285	0	963	375
Geothermal	1	0	0	0	0	33	0	0	0	0
Coal	933	339	4304	0	5544	42624	1698	0	10607	2469
Natural gas	2834	4401	243	288	1073	1058	841	0	27604	378
Oil	236	171	0	0	0	3882	665	1578	2713	1312
Coal CHP	238	131	603	0	3856	7703	3150	0	25	2008
Natural gas CHP	2054	1706	556	41	1027	31229	2100	267	2848	1233
Oil CHP	98	66	0	0	0	0	386	120	576	392
Biomass CHP	464	338	0	275	709	7910	275	97	0	1748

[5] Numbers in parenthesis are storage capacities in GWh

Supplementary Table S58: Installed capacity in 2015 in MW (FR-MT)

	FR	GR	HR	HU	IE	IT	LT	LU	LV	MT
Nuclear	63130	0	0	1887	0	0	0	0	0	0
Hydropower (REG)	16507	2233	1776	38	174	13908	99	1300	1511	0
Hydropower (ROR)	2021	223	33	19	42	3173	29	34	26	0
PHS[6]	6985 (184)	699 (21)	281 (2.34)	0	292 (2)	7833 (68.3)	900 (10.80)	1296 (4.92)	0	0
Onshore Wind	10831	1613	429	329	2670	8750	262	54	51	0
Offshore wind	6	0	0	0	25	0	0	0	0	0
Solar PV	6549	2429	44	6	0	19100	69	116	0	22
Solar CSP	0	0	0	0	0	0	0	0	0	0
Wave	0	0	0	0	0	0	0	0	0	0
Tidal	240	0	0	0	0	0	0	0	0	0
Biomass	43	51	0	143	162	3700	0	22	0	0
Geothermal	0	46	0	0	0	869	0	0	0	0
Coal	4640	4356	325	1070	1148	5422	0	0	0	0
Natural gas	4107	2394	453	2623	3870	41966	2256	54	48	0
Oil	6493	490	853	410	973	11040	0	0	0	462
Coal CHP	170	103	0	29	212	566	0	0	0	0
Natural gas CHP	2014	2519	290	1601	93	4385	432	495	1088	0
Oil CHP	177	228	97	0	0	1153	198	0	0	0
Biomass CHP	1684	0	45	143	0	780	98	0	82	0

[6] Numbers in parenthesis are storage capacities in GWh

Supplementary Table S59: Installed capacity in 2015 in MW (NL-UK)

	NL	NO	PL	PT	RO	SE	SL	SK	UK
Nuclear	492	0	0	0	1298	9528	696	1940	9374
Hydropower (REG)	34	29130	246	4043	5872	14676	896	1535	4026
Hydropower (ROR)	3	2242	288	372	598	1280	157	82	274
PHS[7]	0	1273 (400)	1406 (11)	1029 (107)	285 (10.2)	99 (72)	180 (0.5)	916 (4)	2744 (33)
Onshore Wind	2646	873	3758	4486	2896	5827	3	3	8052
Offshore wind	520	2	0	0	0	202	0	0	5100
Solar PV	1429	0	14	429	1101	0	262	532	9000
Solar CSP	0	0	0	0	0	0	0	0	0
Wave	0	0	0	0	0	0	0	0	0
Tidal	0	0	0	0	0	0	0	0	0
Biomass	1041	0	644	83	92	1251	51	0	1163
Geothermal	0	0	0	0	0	0	0	0	0
Coal	5507	0	20670	1756	4431	136	859	269	17847
Natural gas	10470	0	258	4152	1663	446	418	0	26358
Oil	0	0	345	47	0	1514	0	0	1832
Coal CHP	1990	0	7123	0	1441	189	369	1161	149
Natural gas CHP	9347	1598	726	567	3198	622	72	1199	5211
Oil CHP	0	0	0	0	0	2109	0	301	17
Biomass CHP	455	0	169	499	0	1742	41	365	119

[7] Numbers in parenthesis are storage capacities in GWh

4.2. Electricity generation

Supplementary Table S60: Electricity generation in 2015 by country and technology (all numbers in TWh)

	AT	BE	BG	CH	CZ	DE	DK	EE	ES	FI
Nuclear	0	24.6	14.3	22.1	25.3	86.8	0	0	54.8	22.3
Hydropower (REG)	36.5	1.3	4.7	36.9	3.7	15.8	0	0	27.4	15.0
Hydropower (ROR)	3.7	0.1	1.6	2.7	1.5	7.9	0	0	3.4	1.6
PHS	-	-	-	-	-	-	-	-	-	-
Onshore Wind	5.2	3.2	1.4	0.1	0.6	73.8	9.4	0.7	48.1	2.3
Offshore wind	0	2.0	0	0	0	1.9	4.7	0	0	0
Solar PV	0.4	3.0	1.4	0	2.2	35.2	0.6	0	13.3	0
Solar CSP	0	0	0	0	0	0	0	0	0	0
Wave	0	0	0	0	0	0	0	0	0	0
Tidal	0	0	0	0	0	0	0	0	0	0
Biomass	0	3.5	0.2	0	0	4.2	0	0	4.6	1.9
Geothermal	0.0	0	0	0	0	0.3	0	0	0	0
Coal	3.0	2.9	17.1	0	20.7	211.8	2.2	0	53.0	3.5
Natural gas	7.8	15.8	0.4	1.9	2.6	2.1	1.1	0	44.4	1.4
Oil	1.0	0.5	0	0	0	5.8	0.1	6.2	11.4	0.7
Coal CHP	0.9	1.1	2.7	0	16.3	43.5	5.0	0.0	0.1	3.3
Natural gas CHP	5.1	6.0	0.9	0.3	2.3	56.3	2.4	1.1	4.2	4.3
Oil CHP	0.3	0.2	0	0	0	0	0.1	0.3	0.1	0.1
Biomass CHP	2.5	1.3	0	2.0	1.9	34.3	2.3	0.8	0.0	8.8

Supplementary Table S61: Electricity generation in 2015 by region and technology (all numbers in TWh)

	FR	GR	HR	HU	IE	IT	LT	LU	LV	MT
Nuclear	416.8	0	0	14.9	0.0	0	0	0	0	0
Hydropower (REG)	52.3	5.5	5.6	0.1	0.9	36.3	0.8	1.5	1.9	0
Hydropower (ROR)	5.5	0.6	0.1	0.1	0.2	8.3	0.2	0.0	0.0	0
PHS	-	-	-	-	-	-	-	-	-	-
Onshore Wind	23.4	3.7	0.8	0.7	6.5	14.7	0.8	0.1	0.1	0
Offshore wind	0.0	0	0	0	0.1	0	0	0	0	0
Solar PV	7.4	3.6	0	0	0	23.9	0.1	0.1	0	0.0
Solar CSP	0	0	0	0	0	0	0	0	0	0
Wave	0	0	0	0	0	0	0	0	0	0
Tidal	0.5	0	0	0	0	0	0	0	0	0
Biomass	0.2	0.2	0	0.8	0.2	15.6	0	0.1	0	0
Geothermal	0	0.4	0	0	0	5.7	0	0	0	0
Coal	8.3	18.9	2.1	5.8	6.0	35.8	0	0	0	0
Natural gas	15.3	3.7	0.5	2.1	11.3	103.2	2.0	0.1	0.1	0
Oil	3.3	0	0.2	0	0	8.4	0	0	0	2.6
Coal CHP	0.3	0.5	0	0.2	1.3	4.2	0	0	0	0
Natural gas CHP	6.8	3.6	0.3	1.1	0.2	9.9	0.4	0.7	2.5	0
Oil CHP	0.1	0	0	0	0	0.6	0.0	0	0	0
Biomass CHP	7.7	0	0.3	0.8	0	3.3	0.4	0	0.4	0.8

Supplementary Table S62: Electricity generation in 2015 by region and technology (all numbers in TWh)

	NL	NO	PL	PT	RO	SE	SL	SK	UK
Nuclear	4.0	0	0	0	10.7	54.3	5.4	14.1	65.7
Hydropower (REG)	0.1	129.1	1.2	8.8	15.0	68.1	3.5	4.1	7.5
Hydropower (ROR)	0.0	9.9	1.3	0.8	1.5	5.9	0.6	0.2	0.5
PHS	-	-	-	-	-	-	-	-	-
Onshore Wind	5.6	2.5	10.5	11.3	7.0	16.6	0	0	20.7
Offshore wind	1.5	0.0	0	0	0	0.8	0	0	17.2
Solar PV	0.1	0	0	0.8	2.0	0	0.2	0.5	7.5
Solar CSP	0	0	0	0	0	0	0	0	0
Wave	0	0	0	0	0	0	0	0	0
Tidal	0	0	0	0	0	0	0	0	0
Biomass	2.8	0	5.3	0.4	0.5	4.1	0.1	0	1.3
Geothermal	0	0	0	0	0	0.0	0.0	0	0
Coal	11.8	0	91.5	13.7	13.2	0.2	2.6	0.4	94.1
Natural gas	39.5	0	1.3	8.7	2.5	0.6	0	0	80.4
Oil	0	0	0.2	0.1	0	0.4	0	0	0
Coal CHP	4.9	0	35.8	0	4.9	0.3	1.3	2.1	0.9
Natural gas CHP	32.2	3.5	3.3	1.1	4.4	0.7	0	1.8	14.5
Oil CHP	0	0	0	0	0	0.4	0	0.3	0
Biomass CHP	1.2	0	1.4	2.2	0	5.7	0.1	1.1	0.1

4.3. Nuclear Phase Out

As of 2015, 15 European countries have nuclear power plants in operation. Following the Fukushima accident in 2011, the future of nuclear energy has been heavily debated and three countries pledged to entirely phase out nuclear. Germany closed eight ageing reactors in 2011, with the remaining fleet to be phased out by 2022. Belgium have scheduled a complete phase out by 2025, whereas Switzerland has set 2034 as their target. Supplementary Table S63 shows the current nuclear policy in each of the countries included in TIMES-Europe (from [63]) .

Of the 15 current countries with nuclear capacity, only the abovementioned three have pledged to phase out nuclear. In some countries projects are stalled due to financial difficulties, some nuclear power plants are soon to be in operation, while some countries have nor phase-out plans nor specific project plans.

In TIMES-Europe, the phase out plans of Germany, Switzerland and Belgium are included, whereas linear decommission based on the lifetime of a nuclear power plant is modelled for the other countries. Countries with stated no-nuclear policies are also included (e.g. Denmark, Austria, Italy etc.). Since the median age of nuclear power plants is above 25 years [64], we assume that the whole existing fleet is decommissioned by 2050. Furthermore, since most countries, also those without nuclear capacity today, can invest in nuclear energy, no future plans are included in the model. This is also due to the many uncertain projects, where the operation date might be profoundly extended.

Supplementary Table S63: Nuclear phase out policy in European countries, retrieved from [63] and up to date as of 2015. Newer legislations are updated, with references indicated in text.

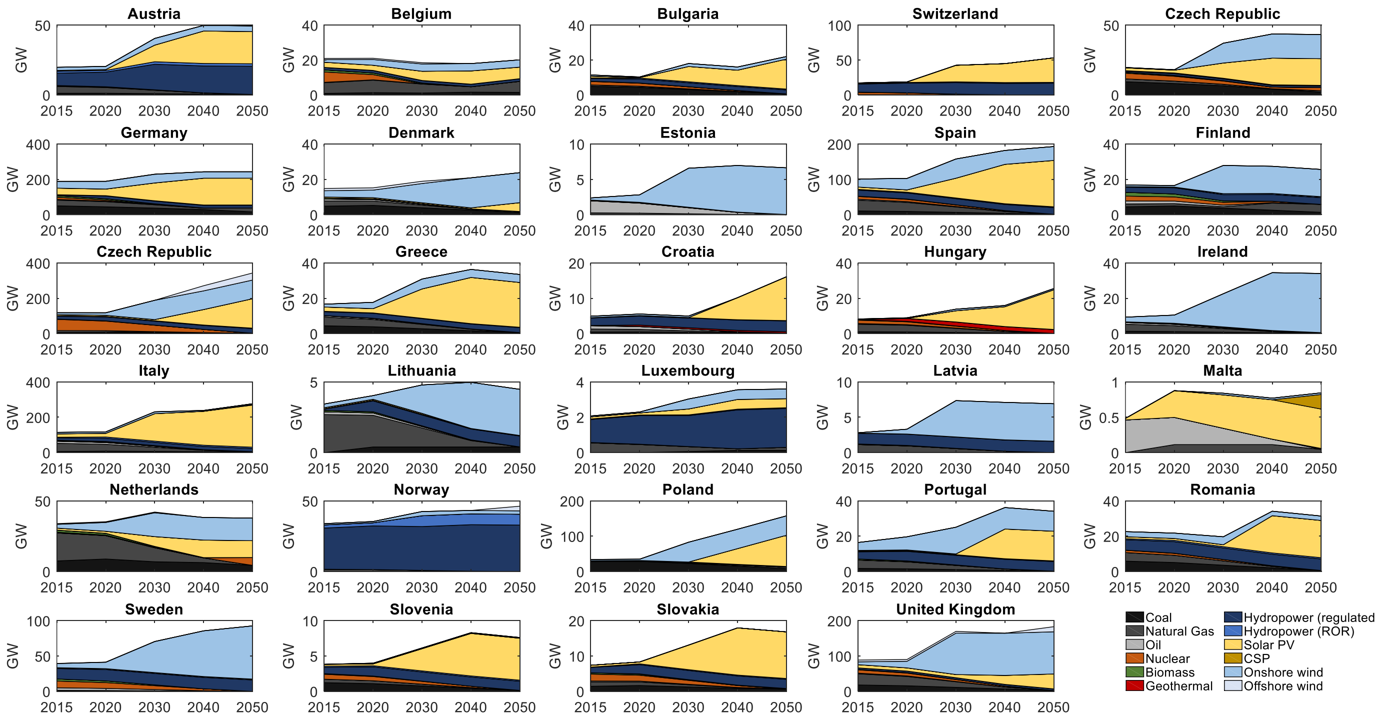
Country	Policy	Planned change
Belgium	Phase-out by 2025	855 MW phase out by 2015, 5066 MW phase-out by 2025
Bulgaria	No phase-out policy	Wants to extend lifetime of current reactors. The Bulgarian parliament decided on June 8th, 2018, to work towards restarting the 2000 MW Belene nuclear project [65].
Czech Republic	No phase-out policy	Wants to extend nuclear fleet, but faces financing difficulties [66]
Finland	No phase-out policy	Several projects planned or under construction. Current fleet has operating licenses until 2018 (1820 MW), and until 2027-2030 (1040 MW). New plant, 1600 MW expected operational in 2018 [67].
France	Reduction policy	Goal of reducing share of electricity from nuclear to 50 % in 2025 (from about 75 % today).
Germany	Phase out by 2022	About 20 GW installed capacity in 2010. 8 plants (8 GW), were shut down in 2011. 12 GW capacity in 2015, about 8 GW in 2020 [68].
Hungary	No phase-out policy	New reactors are planned
Italy	No nuclear reactors	Referendum in 2011 rejected plans to revive the nuclear industry
Lithuania	No nuclear reactors	Plans for a new nuclear power plant, but with an uncertain future.
Netherlands	No phase-out policy	Previous decision to phase-out nuclear was reversed. One power plant in operation, scheduled to decommission in 2033. New projects on hold due to financial issues.

Poland	No nuclear reactors	In 2005 Poland decided to build nuclear power plants, and have plans for two new plants. In 2018, PGE decided to move away from building the first nuclear power plant and invest in offshore wind energy instead [69].
Romania	No phase-out policy	Two reactors planned
Slovakia	No phase-out policy	New reactors are planned
Slovenia	No phase-out policy	Further expansions are under consideration, but not confirmed
Spain	No phase-out policy	Uncertain political situation, no confirmed plans for new reactors.
Sweden	No phase-out policy	Ringhals 1 (860 MW) and 2 (870 MW) to be closed by 2020.
Switzerland	Phase-out by 2034	About 3300 MW capacity in 2015, About 2200 in 2020, 1200 in 2030 and complete phase-out by 2034.
United Kingdom	No phase-out policy	New reactors planned. Government goal of 16 GW new capacity by 2030.

5. Additional results

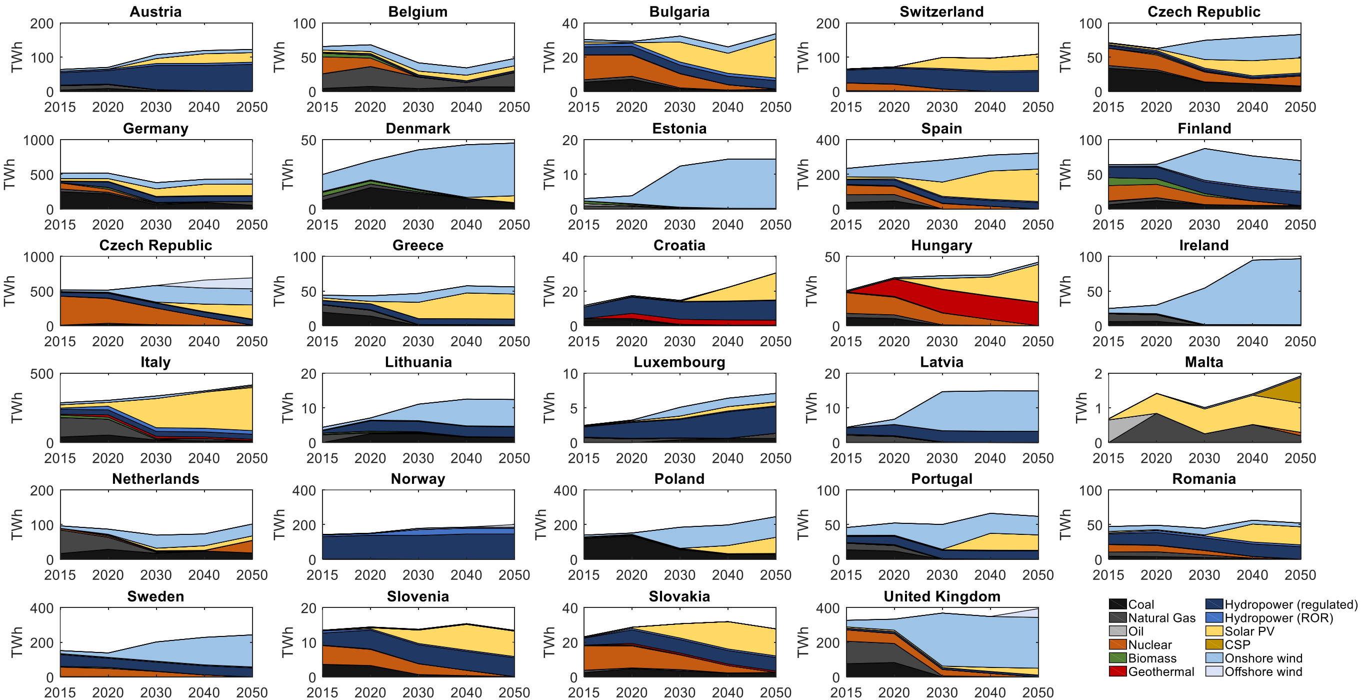
5.1. Detailed model results

Det12 – Installed capacity



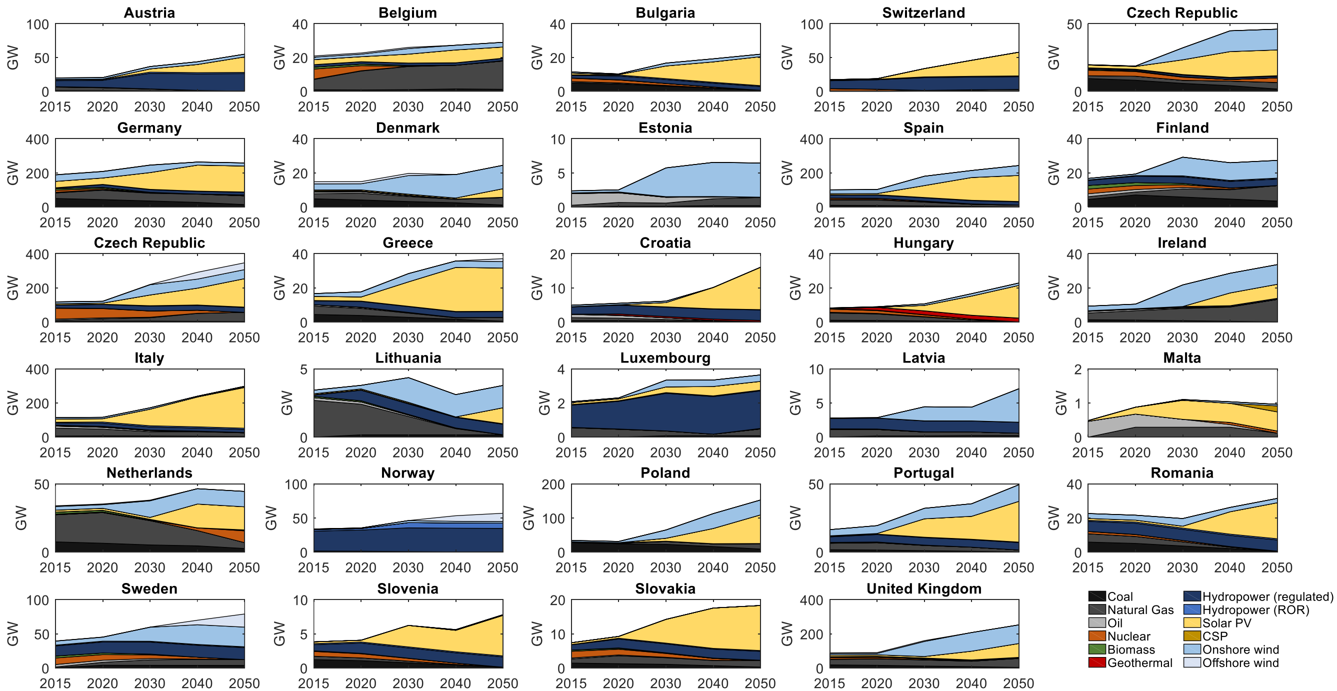
Supplementary Figure S20: Installed capacity – Det12

Det12 – Electricity generation



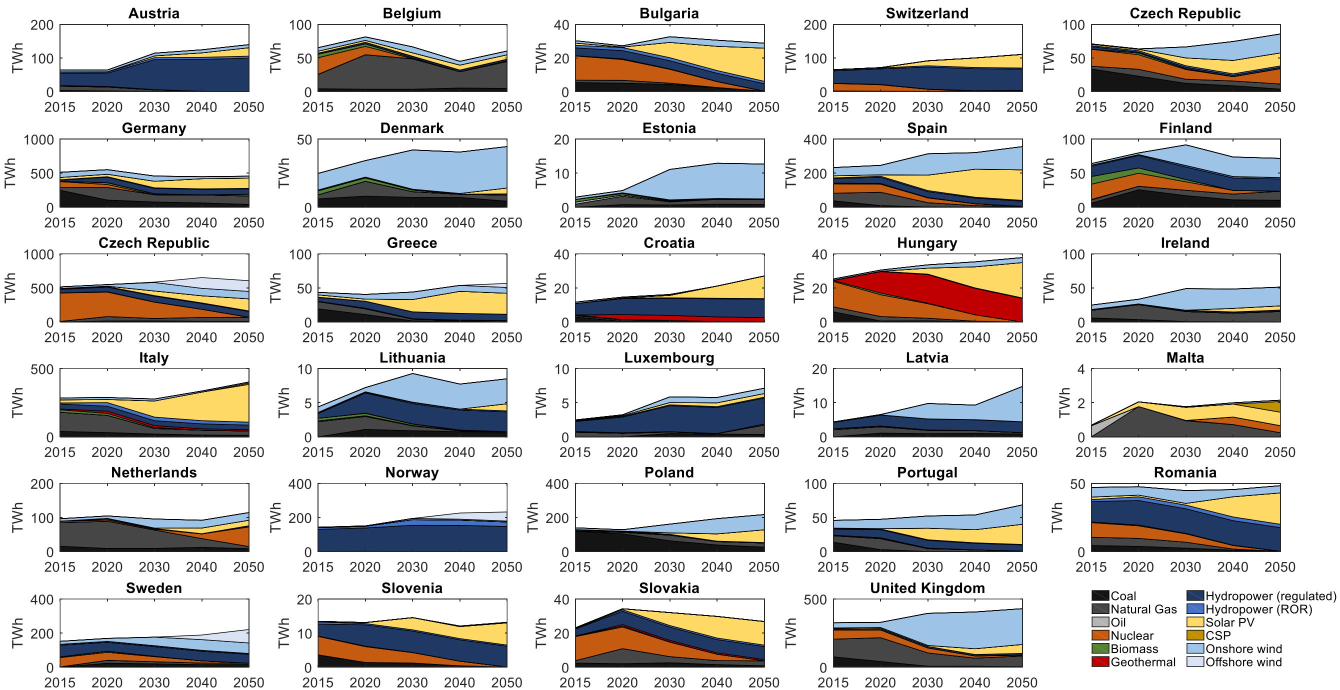
Supplementary Figure S21: Electricity generation – Det12

Stoch12 – Installed capacity



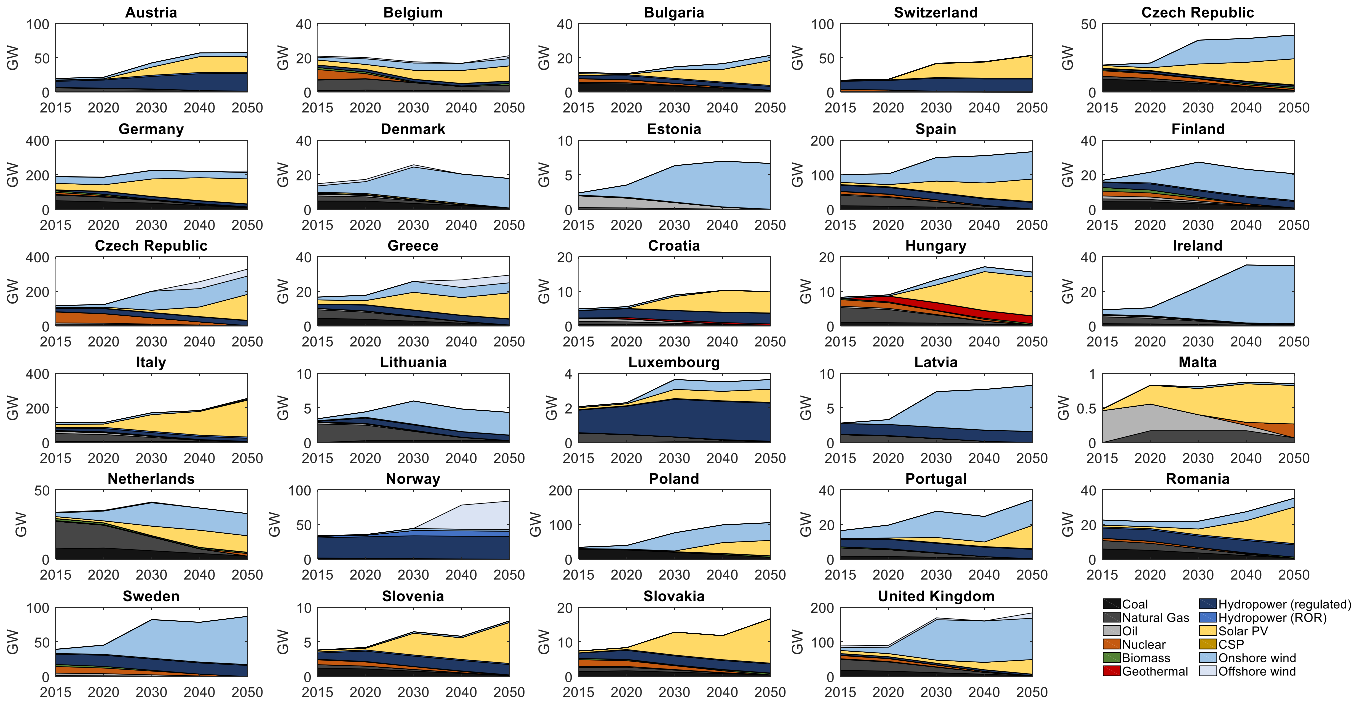
Supplementary Figure S22: Installed capacity – Stoch12

Stoch12 – Electricity generation



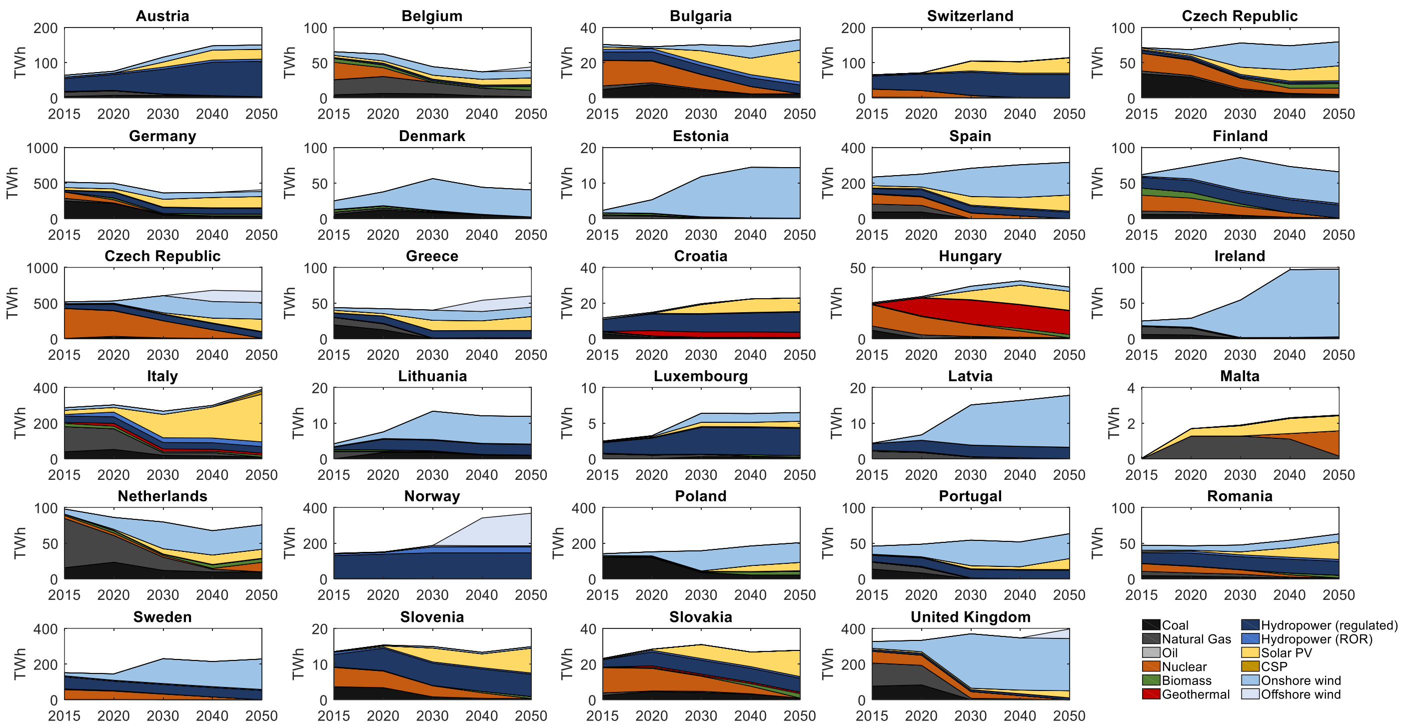
Supplementary Figure S23: Electricity generation - Stoch12

Det48 – installed capacity



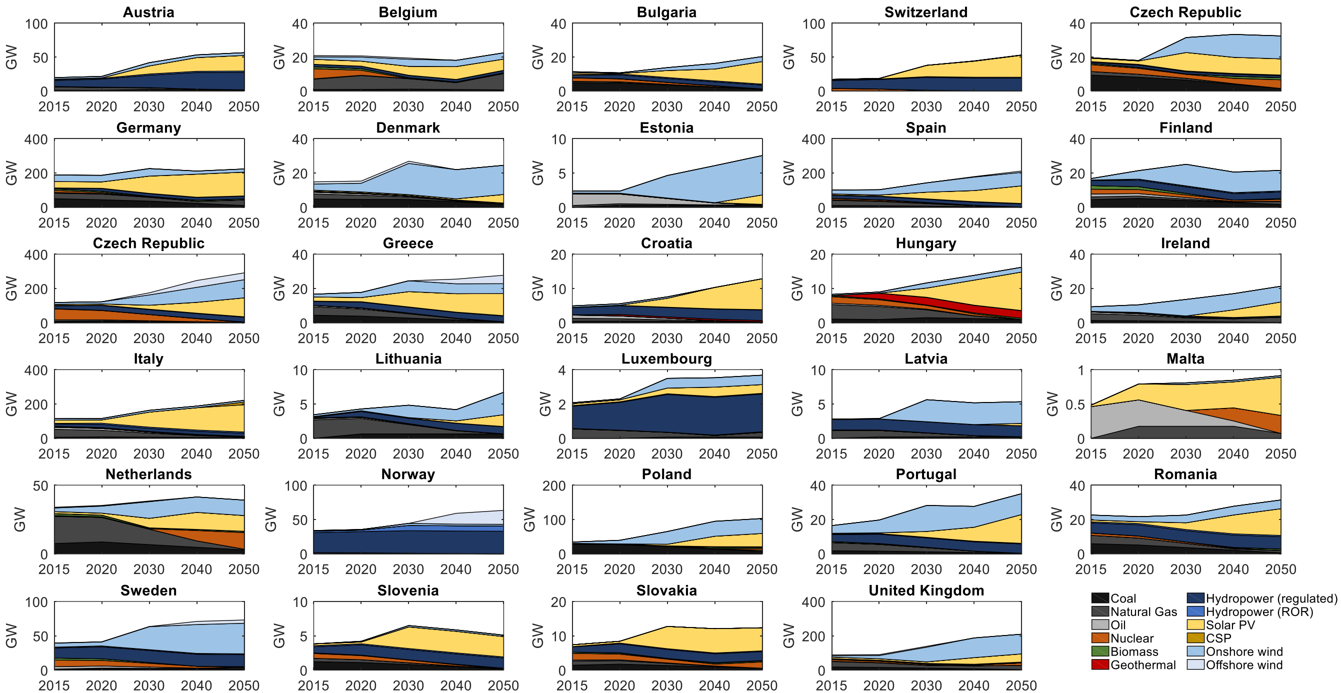
Supplementary Figure S24: Installed capacity - Det48

Det48 – Electricity generation



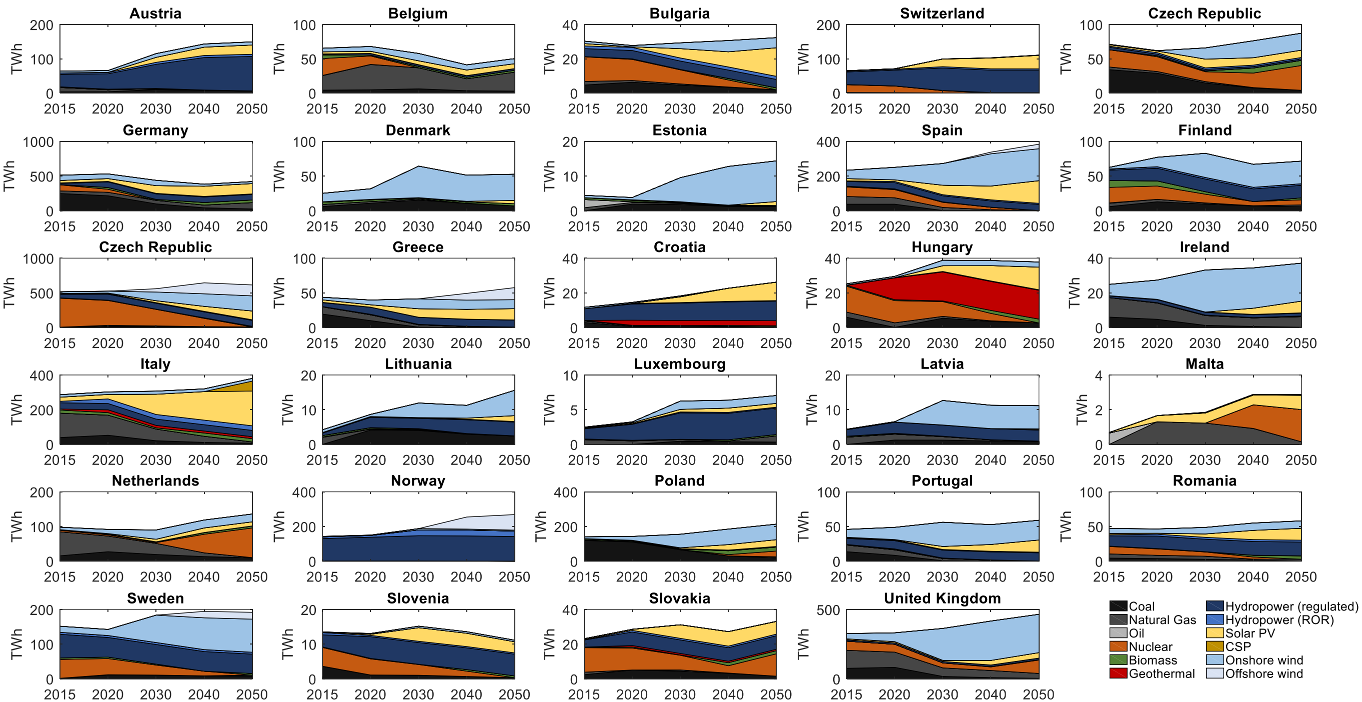
Supplementary Figure S25: Electricity generation – Det48

Stoch48 – Installed capacity



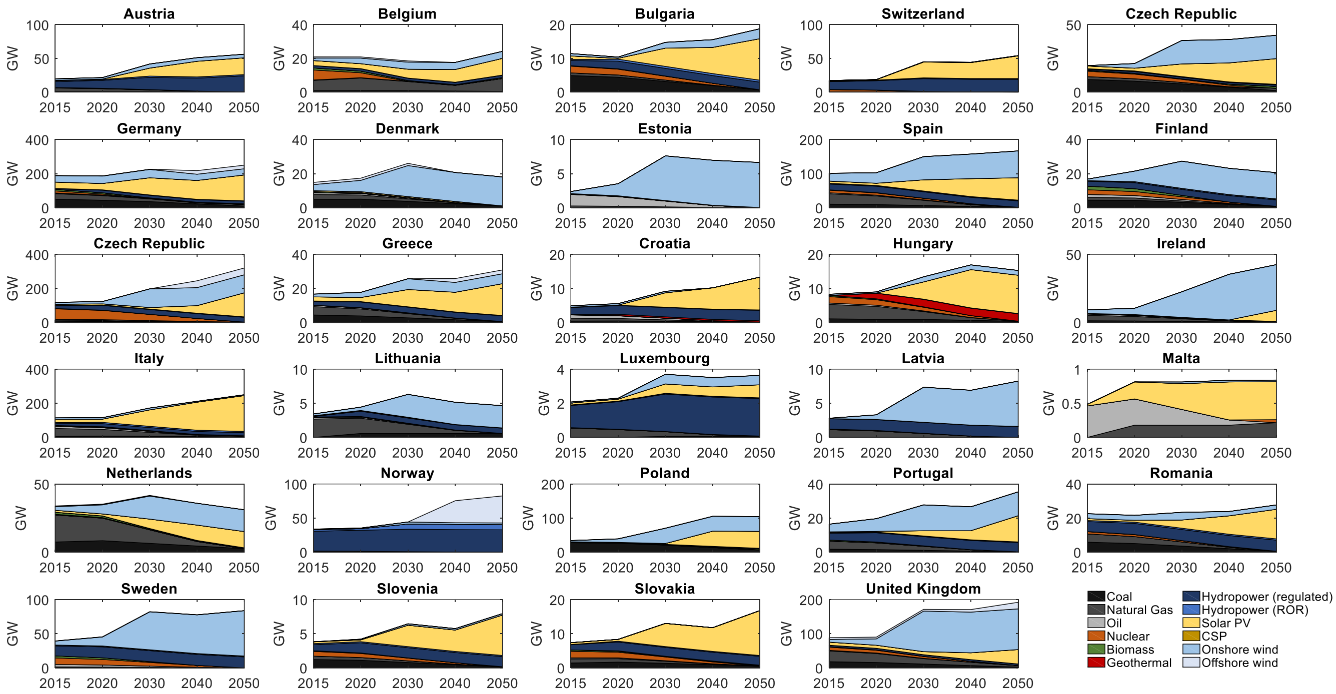
Supplementary Figure S26: Installed capacity -Stoch48

Stoch48 – Electricity generation



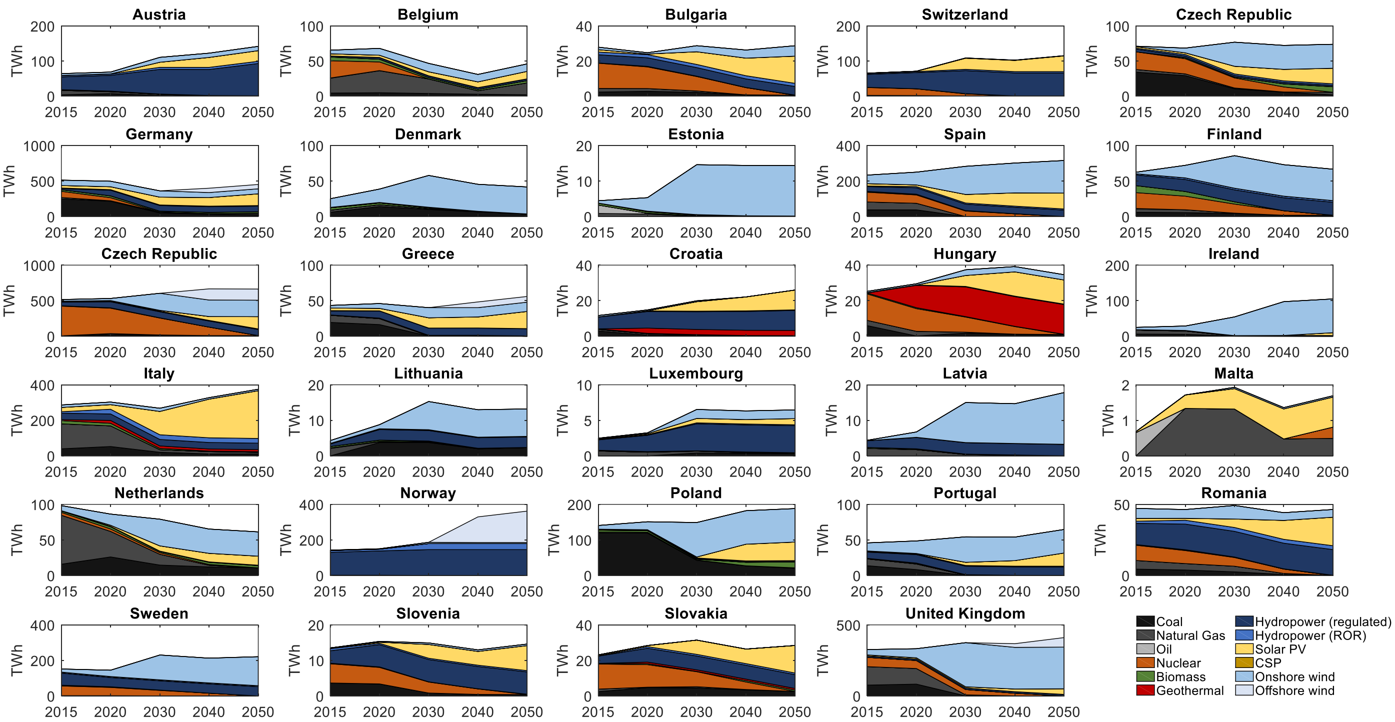
Supplementary Figure S27: Electricity generation - Stoch48

Det192 – Installed capacity

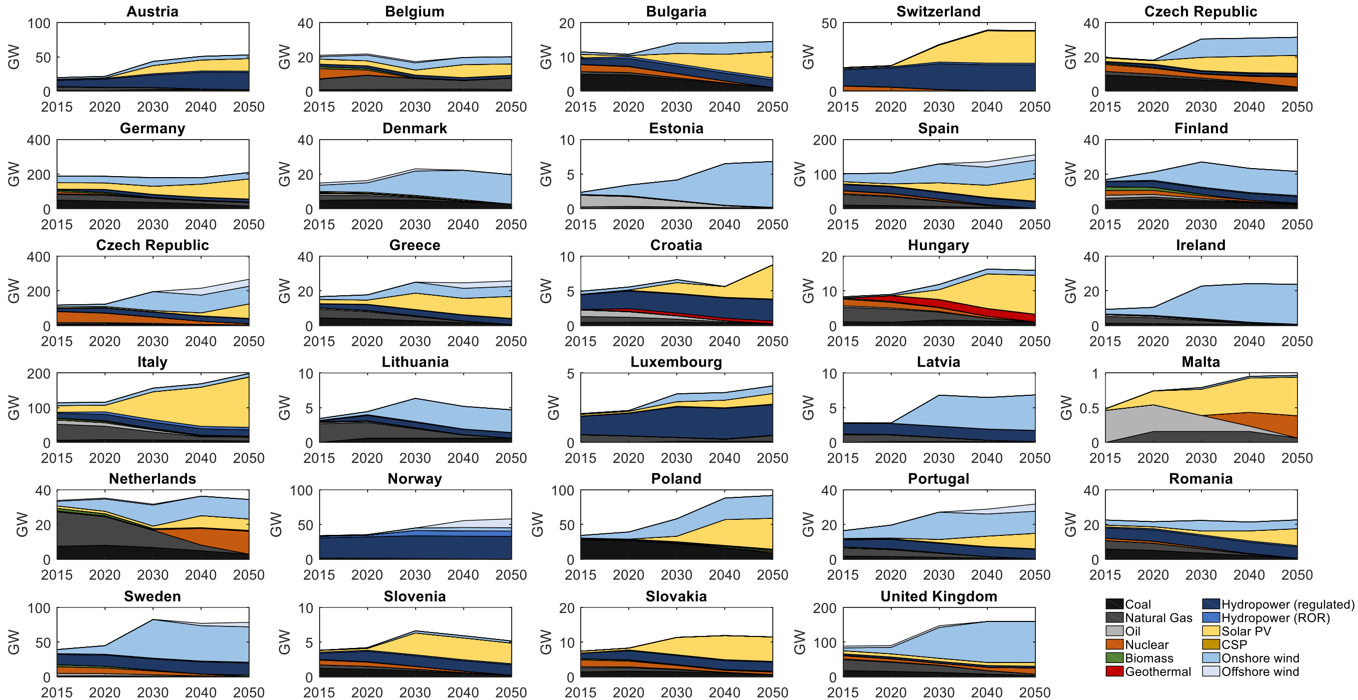


Supplementary Figure S28: installed capacity - Det192

Det192 – Electricity generation

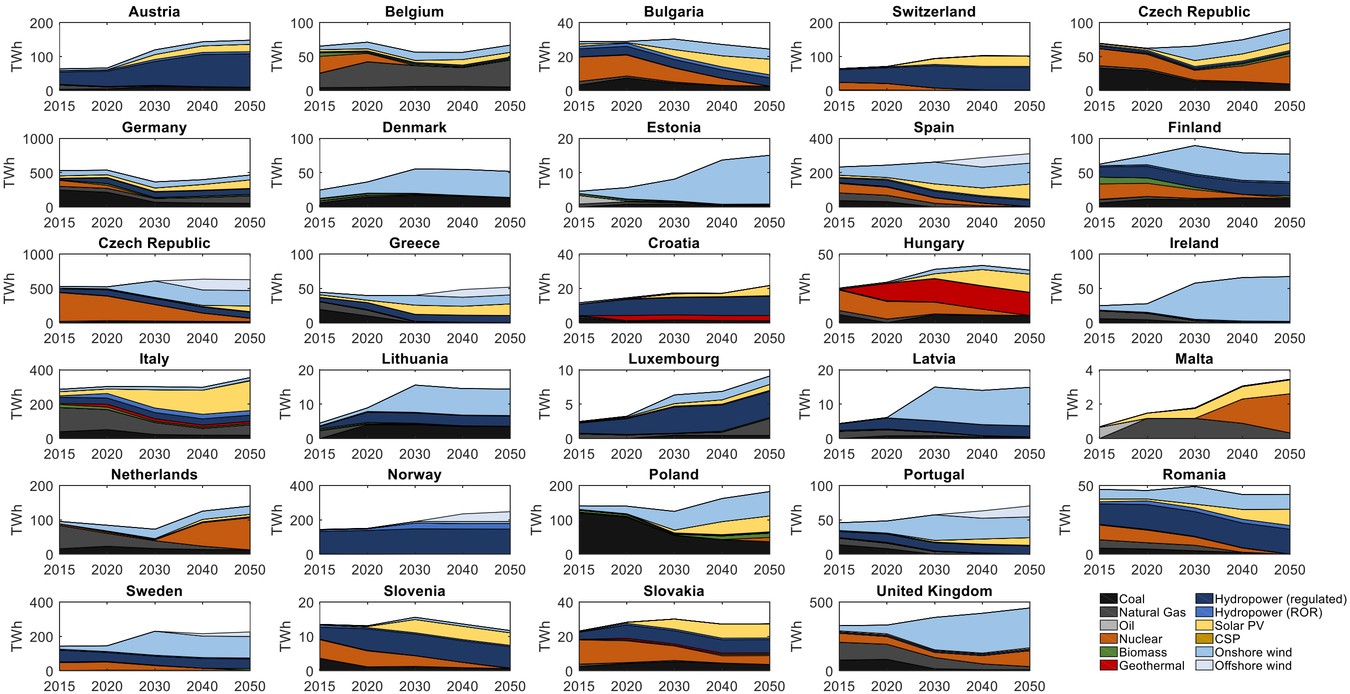


Supplementary Figure S29: Electricity generation - Det192



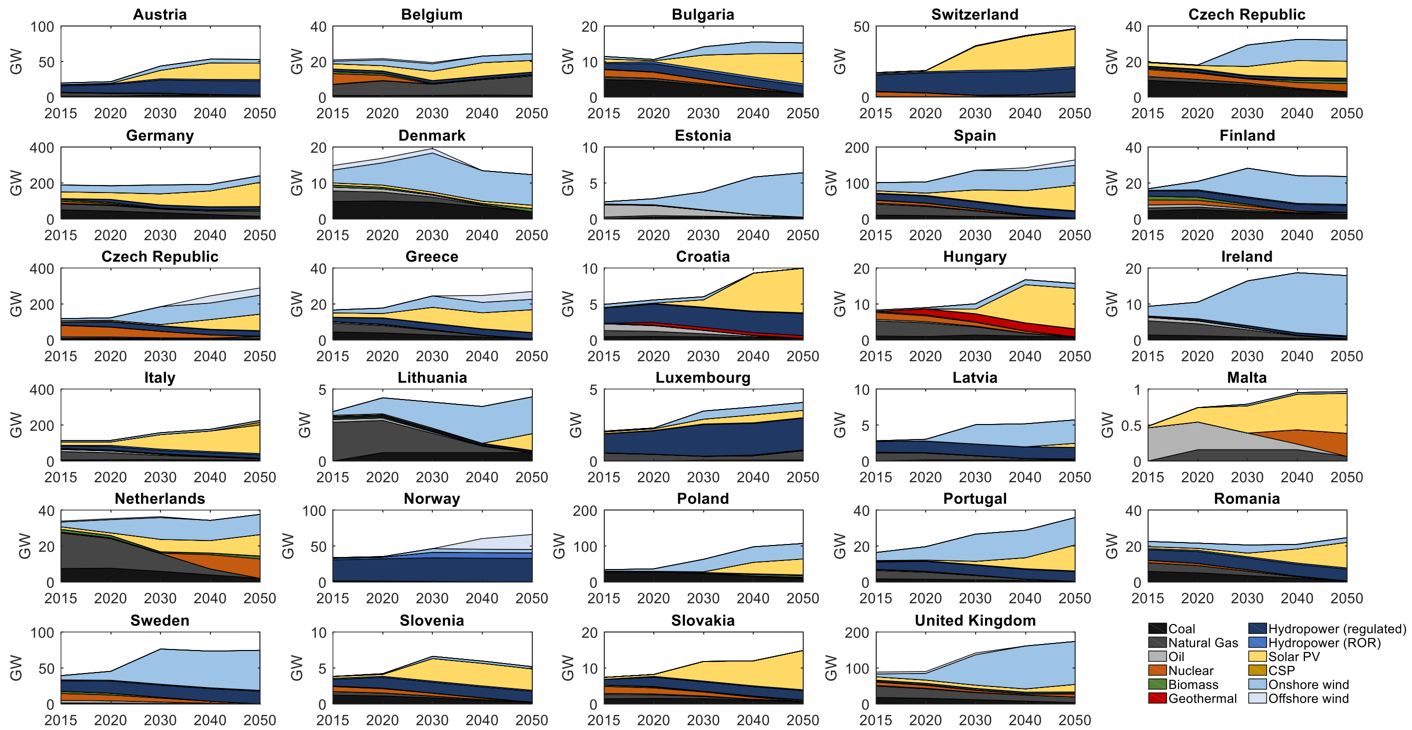
Supplementary Figure S30: installed capacity – Det672

Det672 – Electricity generation



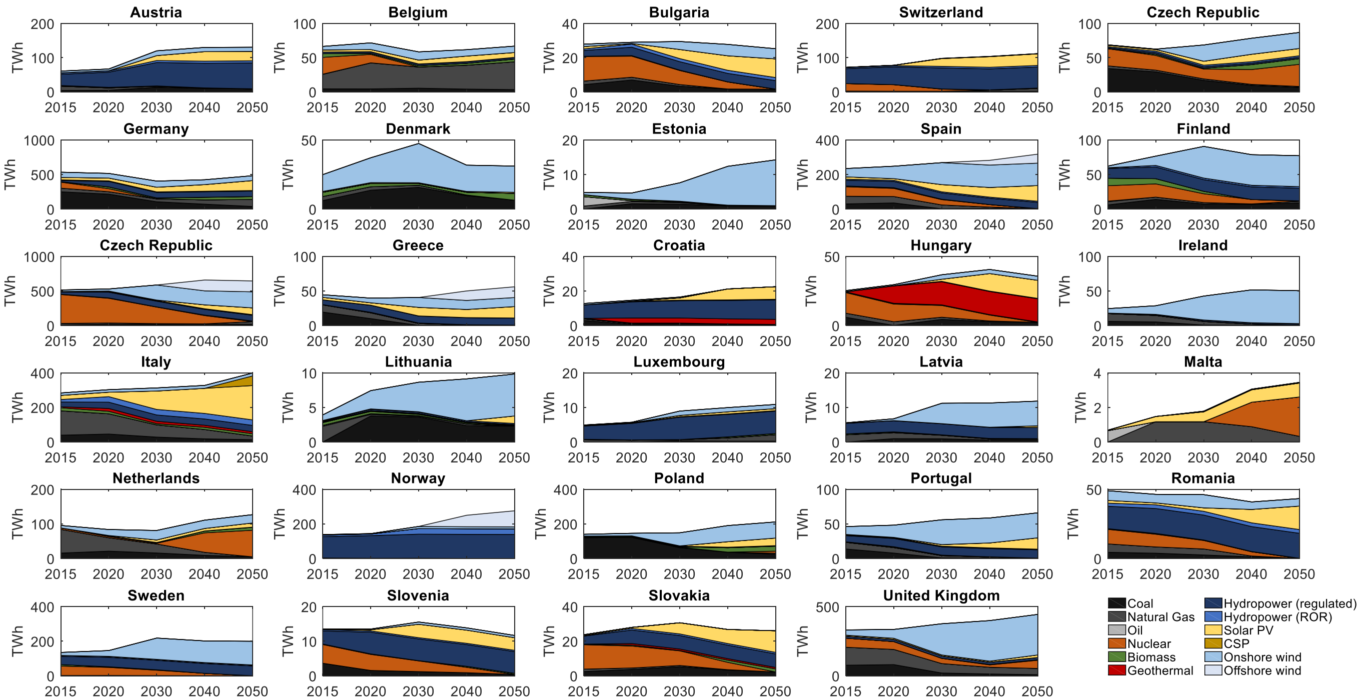
Supplementary Figure S31: Electricity generation - Det672

Det2016 – Installed capacity



Supplementary Figure S32: Installed capacity - Det2016

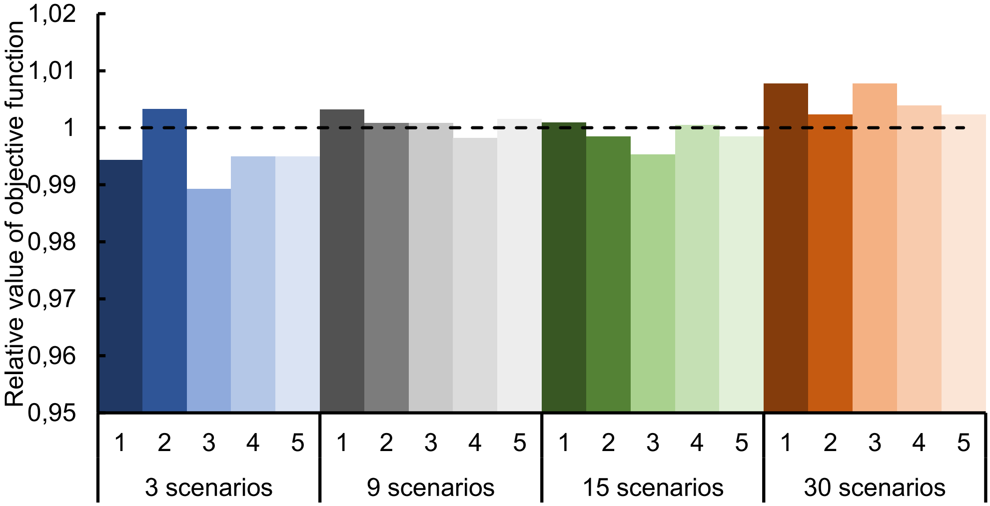
Det2016 – Electricity generation



Supplementary Figure S33: Electricity generation - Det2016

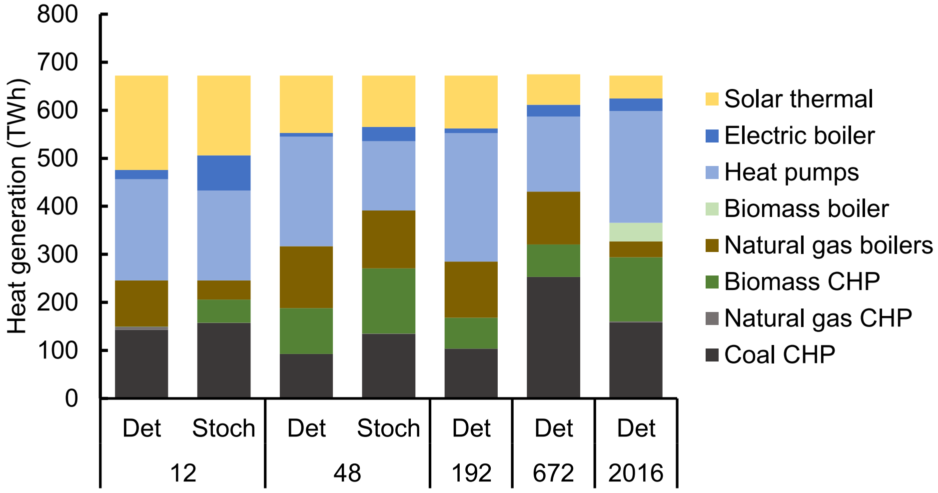
5.2. In-sample stability test

The deviation relative to the objective function value of \textit{Stoch48} ranges between -1 to 0.3 %. For the 5 instances with 15 scenarios, the deviation of the objective function ranges from -0.47 to 0.1 \%. Increasing the number of scenarios to 30 returns an objective function value slightly higher than when using 15 scenarios, but the deviation is only between 0.23 and 0.77 \%. At the same time, increasing the number of scenarios to 30 also drastically increases the solution time. Therefore, given the stability of the solution with 15 scenarios, and the increased computational effort by going to 30 scenarios, we conclude that using 15 scenarios is satisfactory for the purpose of this paper.



Supplementary Figure S34: In-sample stability test

5.3. District heat generation



Supplementary Figure S35: District heat generation (TWh)

5.4. Peak constraint results

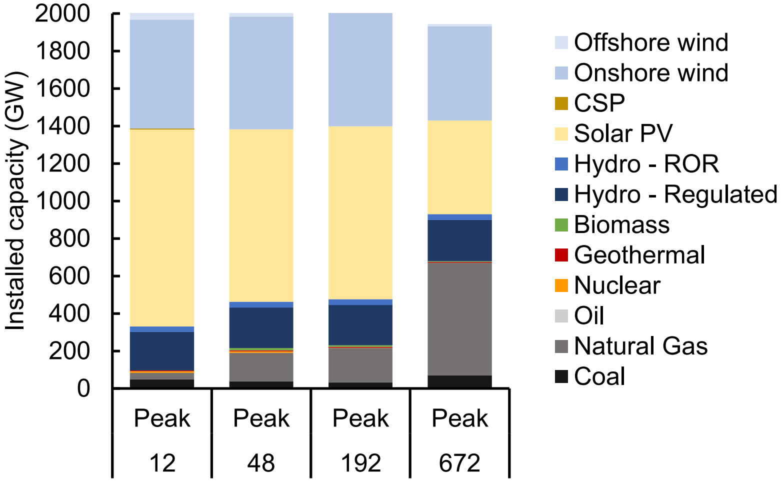
By adding a peaking constraint to the deterministic model version, we can limit the contribution of variable renewables in peaking situations and thus force the model to invest in flexible generation capacity [70]. The peaking constraint is given by:

$$D_{t,p} = \sum \left(p^i * CF_{t,p}^i * cap_p^i\right) + CF_{t,p}^c * cap_p^c$$

Where $D_{t,p}$ is the demand of electricity in time-slice *t* and period *p*, $p^i$is the peaking constraint for variable renewable energy sources (onshore/offshore wind and solar), $CF_{t,p}$is the capacity factor for the variable energy sources *i* and the dispatchable technologies *c*, and finally cap_p^c is the installed generation capacity of each technology in period *p*.

The value of the peaking constraints are decided exogenously, and usually vary between 0-30 percent depending on the technology [17,70,71]. For TIMES-Europe, the peaking coefficients are set individually for every country based on their expected annual capacity factor. As an example, Germany's peaking factors are set to 22 % for onshore wind, 33 % for offshore wind and 12 % for PV. As a result, variable renewables can only cover up to a maximum of 67 % of the peak capacity in Germany, thus forcing investments in flexible generation capacities.

It is important to mention that the peaking constraint does not restrict the contribution of electricity generated from variable renewables to serve the electricity demand, but only ensures investments in flexible reserve capacity such as hydropower or storage. However, the caveat of this approach is that since the peaking constraints are decided exogenously, the requirement of flexible generation capacity is a result of model input rather than an endogenous model decision based on the actual solar and wind variability.



Supplementary Figure S36: Operational peak reserve constraint results

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