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The role of transmission and energy storage in European decarbonization towards 2050

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A R T I C L E I N F O

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A B S T R A C T

This paper presents analyses of the development of the European electricity sector that is in line with the climate and energy targets of the European Union for 2030 and 2050. The role of energy storage and transmission under various assumptions about a) development of electric battery costs, b) transmission grid expansion restrictions, and c) the variability of future electricity demand is demonstrated. Two models are soft-linked – LIBEMOD, a multimarket energy equilibrium model of Europe, and TIMES-Europe, a bottom-up stochastic model of the European electricity and district heat sectors – to provide an analysis of the decarbonization of the electricity sector that has consistent assumptions about electricity use and fuel prices. To explicitly value flexibility, a stochastic methodology is used to ensure that investment decisions take into account different operational situations that can occur due to weather-dependent renewable generation and the uncertainty of the electricity demand. It is demonstrated that the European power sector can be decarbonised with a 65%–70% share of the electricity supply from wind power and PV in 2050. The cost-efficient investment in stationary batteries is highly dependent on technology development in PV and expansion of the international transmission grid.

1. Introduction

The European Union (EU) energy and climate policy aims to cut CO_2 emissions in the power sector significantly by 2030 [1] and to establish a nearly carbon-free electricity sector by 2050 [2]. Increasing wind and solar electricity generation is considered critical to reaching these policy goals. Because of policy instruments directed at these technologies and significant technology improvements, the speed of installation of wind and solar power has increased exponentially during the last decades.

Wind and solar power generation differ from conventional thermal power due to their intermittency; this type of renewable electricity generation is strictly weather dependent and cannot be regulated to match the electricity demand. In general, there are four strategies to reduce the mismatch between intermittent supply and demand. First, **flexible supply**: variation in intermittent supply can be counteracted by production from flexible electricity technologies, such as fossil-based thermal power and hydropower, to obtain a total supply that equals demand. Second, **demand management**: demand can be shifted over time or curtailed. Third, **energy storage**: in periods with a net surplus of electricity, the excess amount of electricity can be stored, for example, in batteries, or used to produce hydrogen. Then in periods with a net deficit of electricity, batteries can be discharged, or hydrogen can be used to produce electricity. Finally, **trade**: the instantaneous mismatch between production and load in a country can be evened out through electricity trade by utilizing national differences in the electricity technology mix, as well as in weather-dependent intermittent generation. In this way, the net surplus in electricity in one country is exported to countries with a net deficit.

The hypothesis of this paper is that the EU energy and climate targets for 2030 and 2050 (i.e., policy goals for energy efficiency, renewables and greenhouse gas (GHG) emission reductions) will increase the capacity of intermittent power, storage technologies and international transmission lines. To be more specific, this paper answers the following research questions:

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1. What is the optimal mix of electricity generation technologies, energy storage and transmission grid in the EU in 2030 and 2050?
2. How does a) technology improvement in wind power, solar PV, and electric batteries, b) future variability in electricity demand, and c) limitations in transmission grid expansions influence the cost-optimal design of the European power market?

To analyse the hypothesis and the associated research questions two numerical models are soft-linked. The first model, LIBEMOD [3], analyses how the EU energy and climate targets for 2030 and 2050 impact future electricity demand. LIBEMOD is a multi-good, multi-period equilibrium model covering the entire value chain of eight energy goods from investment, extraction, and production via trade to consumption in 30 European countries. LIBEMOD, which draws on economic theory, determines all quantities and prices in the European energy markets (electricity, fossil fuels and bio energy) subject to a set of policy targets. In particular, the model determines *equilibrium demand* for all types of energy carriers, including electricity.

Output from LIBEMOD, including country- and year-specific electricity demand, is used as input to the second model, TIMES-Europe; this model has earlier been applied to energy modelling studies, see [4], and was originally developed in [5]. This is a bottom-up, long-term optimization model of the European electricity and district heat sector. To capture the weather-dependent characteristics of wind and solar power, as well as the short-term uncertainty of electricity demand, TIMES-Europe uses stochastic programming. This gives investment strategies that are feasible and cost-optimal for a range of possible future operational situations. TIMES-Europe provides investment decisions for four model periods between 2020 and 2050 for electricity production capacities, (e.g. coal power, hydro, wind power and solar), storage technologies (batteries and hydrogen), and the European transmission network. In addition, the model determines hourly operation of capacities.

LIBEMOD has a temporal resolution of eight periods throughout the year, which can be insufficient to address the amount of flexibility needed to handle ambitious climate targets. In contrast, TIMES-Europe has a higher temporal resolution: a year consists of 48 time slices. Because these are combined with 15 scenarios, 720 (48×15) different operational situations can materialize during one model year. LIBEMOD determines demand for electricity, whereas TIMES-Europe takes demand for electricity as an exogenous input. These two factors (temporal resolution and electricity demand) are the main reasons to soft link the two models, thereby ensuring that outputs from TIMES-Europe represent investment and operational decisions in the electricity sector that are consistent with EU policy goals.

The main research contribution of this paper is to derive the cost-efficient mix of intermittent technologies, flexible supply technologies, energy storage technologies, and international electricity transmission needed to meet the EU energy and climate targets for 2030 and 2050. In particular, the cost-optimal trade-off for investment in i) different types of power plants (e.g., conventional stations vs. renewables with intermittent dispatch), ii) different types of energy storage technologies (batteries vs. hydrogen), and iii) the international transmission capacity that is needed to meet the EU energy and climate targets is found. To this end, a stochastic modelling framework that explicitly captures the short-term uncertainty of intermittent supply and hourly electricity demand is used.

The research contributions in the context of the literature are further elaborated in Section 2. The remainder of this paper is structured as follows: Section 3 gives an overview of the data and methods applied. Section 4 provides information on key modelling assumptions while Section 5 presents and discusses the modelling results. Section 6 concludes.

2. Research contributions and literature review

This paper contributes to two strands of the literature: i) the future European electricity market and the role of international transmission and energy storage in achieving GHG emissions targets, and ii) modelling of electricity markets with substantial intermittent supply. Below, a literature review that highlights our contribution to the literature is provided.

There is a substantial literature on the future European electricity market: The PRIMES energy system model is used in [6] to assess various scenarios where GHG emissions in the EU in 2050 are cut by 80%. The LIMES-EU^{+} model with 29 European countries, as well as countries in North Africa and the Middle East, is used in [7] to examine a 90% emission reduction by 2050. To assess alternative renewable shares in electricity consumption in 2030, and how the cost-effective renewable share depends on technology characteristics [8], uses the LIMES-EU model. The elesplan-m power system model is used in [9] to examine cost-effective pathways towards 2050 for all ENTSO-E member states under the restriction that by 2050, GHG emissions in the electricity sector are reduced by 98.4% relative to 1990. To examine effects of a 95% reduction in CO_2 emissions in 30 European countries [10], uses the perfect foresight PyPSA-Eur-Sec-30 model. Finally [11], a PRIMES study commissioned by the EU Commission, examines the 2030 EU Climate and Energy Package from 2018.

In the studies referred to above, total costs of investment and electricity production are minimized, and demand for energy or electricity is taken as given. These studies use external sources that offer demand predictions for future years. To our knowledge, there is no check of consistency between the study producing the demand forecast and the energy study using these demand estimates. In contrast, our study soft-links two models to ensure consistency between policy targets and demand: the electricity model TIMES-Europe uses demand predictions from LIBEMOD that are derived under the same policy restrictions as those imposed in TIMES-Europe. This represents a novelty of the modelling framework.

Second, the studies above focus either on policy target(s) for 2030 or on emissions in 2050. In contrast, this paper assumes that all EU energy and climate targets for 2030 *and* the 2050 EU emission target are met. Furthermore, except for [10], the studies above either neglect or do not adequately model battery and hydrogen storage technologies—these technologies can be decisive in managing electricity markets with substantial intermittent supply. In [7], the deterministic LIMES-EU^{+} model contains two generic storage technologies: one allowing for “day/night storage” and another for “day to day storage”. In [9], the modelling of storage technologies is simplified as these are represented by “a single efficiency parameter reflecting accumulated losses in several process steps”. However, our study includes several types of storage technologies, for example, lithium-ion batteries, adiabatic compressed air energy storage, underground thermal energy storage, hydrogen, reservoir hydro and pumped hydro storage.

Finally, the studies listed above use deterministic energy models, thereby providing investment decisions that considers one operational situation only. As opposed to a deterministic model, a stochastic modelling approach takes into consideration the possibility that a range of operational situations may materialize in the future, for example, due to short-term weather uncertainty. The stochastic approach is used to explicitly capture the need for flexibility by searching for investments that are feasible and cost optimal for the range of possible future states. As demonstrated in e.g. [12], using a deterministic or a stochastic modelling approach can indeed influence the model result. For example, in [13] it is demonstrated that a deterministic investment strategy in the decarbonization of an Artic settlement is not capable of meeting the energy demand as this modelling approach overestimates the contribution from wind energy. In contrast, this paper addresses the role of flexibility in a European power market using a stochastic modelling approach to characterize the short-term uncertainty of supply and demand.

Only a small share of long-term energy system models applies a stochastic modelling approach. Most long-term energy models use a deterministic approach and hence consider one operational situation only. In the following, three stochastic energy models are compared with our modelling approach.

To explore the role of intermittent supply [14], uses the stochastic, multistage, cost-minimizing dispatch and investment model DIMENSION for Central Europe. The paper examines how alternative assumptions about the market share of intermittent power affect investment in electricity generation capacity. Whereas [14] assumes exogenous prices of CO_2 emissions for the whole planning period 2008 to 2050, in our study the agreed upon emission targets for 2030 and 2050 are imposed. Also, our study covers more countries than those located in Central Europe, as well as more technology options, for example, more types of electric batteries. Finally, whereas [14] studies policy uncertainty as to whether renewable targets will be reached, the present study focuses on uncertainty in demand and weather conditions. A key result in [14] is that relative to perfect foresight, policy uncertainty lowers investment in storage technologies. In contrast, our results suggest that relative to no uncertainty, stochasticity in demand and weather conditions triggers investment in storage technologies.

The stochastic, cost-minimizing European power model E2M2 in [15], which partly extends the basic model in [16], determines investment and supply of electricity for a number of technologies, including wind, solar and hydro, under scenarios that differ with respect to parameter values for demand, fuel prices and CO_2 emissions.

While there are similarities between [15] and our paper, there are also important differences. First, the modelling of time differs somewhat. In the E2M2 model, each season is represented by two standard days, which are divided into seven time segments with time resolution varying between 1 h and 6 h. In TIMES-Europe, each of the four seasons (in each country) is represented by 12 2-h blocks, and there are 15 stochastic scenarios for each 2-h block.

Second [15], does not contain a battery storage technology, which may have an important role in the future technology mix. In fact, a key goal of our paper is to study the trade-off between investment in electricity generation and storage. Third, the capacities of interconnectors are fixed in [15], whereas in our paper these capacities are determined as part of the cost-minimization problem. Because the case of no investment in international transmission lines is also considered in our study, the importance of international network investment and the trade-off between investments in hydropower, international transmission capacity and batteries can be examined.

In [17], the stochastic EMPIRE model is used to study how demand responses, aimed at reducing peaks in consumption and transmission, impact the European electricity market when CO_2 emissions are imposed to decrease linearly over time until they have been cut by 90% in 2050. The present study has a different aim, namely to identify how EU policy targets for energy and emissions impact the European electricity markets (when there is no investment in demand management) and also how the outcome of the European electricity market depends on whether there is cost-efficient investment in international transmission lines or no transmission investment. Also [17], does not clearly describe their modelling of storage technologies, making a comparison with our study difficult.

The current article soft-link two models to improve the temporal time resolution and also to ensure consistent demand input in analysing effects of ambitious climate and energy policy targets. In the modelling literature, it is rather common to link models in order to benefit from the strength of a set of models. Typically, the modeller links a model with a fine time resolution to a model that offers a rich representation of technical and economic aspects of the energy/electricity sector. Deane et al. [18] soft-linked TIMES to the power system model PLEXOS to evaluate the appropriateness of the electric power portfolio developed by the Irish TIMES model. They concluded that the linear Irish TIMES model provided a reliable power system but undervalued flexibility elements. Brouwer et al. [19] link a MARKAL energy system model for the Netherlands to a Dutch power market model, and argues that the MARKAL model is inadequate to capture required investment to sustain a high share of renewables. Poncelet et al. [20] soft-linked TIMES to the unit commitment model LYSUM to model the Belgian power system. A key finding is that insufficient representation of solar and wind variability can lead to biased results. Finally, Pavičević et al. [21] soft-linked a long-term, multi-sectoral planning model (JRC-EU-TIMES) to an optimal dispatch model with multiple sectors (Dispa-SET) to examine an European energy system with a high share of renewables.

Whereas the articles referred to above are example of unidirectional linkage, i.e., output from an energy system model is used as input to a power model, there are also studies with bidirectional linkage, i.e., two models modify each other at least once. Some examples are Rosen [22] for the German electricity sector, Pina [23] for the power sector of Portugal, and Seljom et al. [24] for the Norwegian electricity sector. In the energy literature, there are also other types of soft-linking. An early example is Hoffman and Jorgenson [25], where a macro-economic model is coupled with a process analysis model of the energy sector. Drouet et al. [26] soft-linked a model for the residential sector to a macro economic model, whereas a model for the transport sector was soft-linked to a macro model in Schafer and Jacoby [27]. Other examples are Fortes et al. [28], establishing an integrated techno-economic modelling platform by linking TIMES and GEM-E3, and Krook-Riekkola et al. [29], which introduced a soft-linking procedure between a CGE model (EMEC) and an energy system model (TIMES-Sweden).

To summarize, while there are numerous papers investigating the impacts of cutting emissions in the electricity sector, most of them apply a deterministic approach where only one operational situation is considered. Because of the stochastic nature of intermittent supply and the load, these studies can underestimate the need for flexibility, including investment in storage technologies and international transmission capacity. Moreover, the few studies that apply a stochastic approach typically neglect or inadequately model either storage technologies or transmission expansion, or do not include a sound description of all technologies. In contrast, our paper studies the role of different types of stationary batteries and hydrogen in reaching the EU energy and climate targets for 2030 and 2050 under alternative assumptions about demand variability, transmission expansion and costs. Like a number of other studies, (two) models are linked to obtain a fine time resolution. However, for the current study another motivation for linking is to ensure consistent demand input in analysing policy targets. To the best of our knowledge, this is the first study applying linking of models for that purpose.

3. Methodology and assumptions

This section first provides an overview of the EU policy targets for 2030 and 2050. Then it describes the equilibrium model LIBEMOD and the stochastic energy system model TIMES-Europe. Thereafter, it details the stochastic modelling approach and the scenario generation method before presenting the soft-linking of the two models.

3.1. EU policy targets

The EU has for years set ambitious energy and climate targets. This started in 2007 with the triple 20% targets: a 20% cut in GHG emissions (relative to 1990), a renewable share in final energy consumption of 20%, and an improvement in energy efficiency by 20%, see Europa (2020). In 2009, the EU formally adopted the objective to reduce GHG emissions by 80–95% by 2050 in comparison to 1990. Later, the European Commission elaborated sector-specific reduction targets: by 2050, emissions from the electricity generation sector should be reduced by 95% [2].

In 2018, an agreement between the key EU institutions – the Commission, the European Parliament, and the European Council – was reached after a long debate over the 2030 EU climate and energy policy package. The parties agreed to reduce GHG emissions by (at least) 40% (relative to 1990), to reach an EU-wide renewable share in final energy consumption of 32%, and to improve EU energy efficiency by 32.5% (relative to 2005), see [1]. Whereas the ETS sectors (electricity generation, carbon-intensive manufacturing firms, petroleum extraction and most of aviation) have to reduce their GHG emissions by at least 43% relative to 2005, the corresponding reduction for the non-ETS sectors is 30% (relative to 2005).

3.2. The multi-market equilibrium model LIBEMOD

LIBEMOD [3] is a numerical, deterministic, multi-good, multi-period equilibrium model covering the value chain of eight energy goods from investment, extraction, and production via international trade to consumption in 30 European countries. All domestic and international markets are competitive.

In each country, there are four end-user sectors demanding energy goods. This is modelled by a multi-level demand system with constant elasticity of substitution (CES); each end-user sector in each country is represented by a set of CES parameters. Also, each country has an electricity generation sector. There are several technologies available for electricity generation (thermal stations, hydro, intermittent, etc.), and each power producer chooses investment and time-dependent electricity supply to maximize profits, subject to a set of technical constraints. For thermal power plants (nuclear, bio power, coal power, gas power, and oil power), a plant uses one type of fuel only. In each country, there is domestic transportation and distribution of energy.

In LIBEMOD, all emitters of CO_2, in particular, fossil-fuel based power stations, have to pay a price for CO_2 emissions.[1] For the electricity sector, this price, which corresponds to the EU ETS price, is determined from the requirement that total demand for ETS quotas is equal to total supply of ETS quotas, where the latter is part of the EU climate policy. The price for CO_2 emissions is one component in the user price of a fossil fuel. In general, the *user* price of a fuel consists of i) the (model-determined) producer price of this fuel, that is, how much the *producer* of the fuel receives for each unit traded, ii) the (model-determined) price for CO_2 emissions multiplied by the CO_2 emission coefficient of the fuel, iii) other taxes (energy taxes, value-added taxes, etc.), and iv) costs of, and losses in, transport and distribution of the fuel.

The LIBEMOD version applied in this article has cost and efficiency parameters of electricity technologies from the New Policy Scenario in IEA [30], see Tables 1 and 2 in [3]. Parameters in the CES demand system are calibrated, using numerous sources, including estimates for direct price elasticities, cross-price elasticities, and income elasticities, see Aune et al. [31] and LIBEMOD [32] for documentation.

In LIBEMOD, the set of policy targets and the set of instruments that are available for reaching these targets are exogenous ("inputs"). The model finds the combination of policy instruments that is consistent with reaching all policy goals and the associated energy prices and quantities in the European energy markets.

This paper imposes the policy goals of the 2030 EU energy and climate package, and also requires that GHG emissions in the electricity sector are reduced by 95% by 2050, see Section 3.1. In the electricity sector, GHG emissions reductions are accomplished through a different mix and scale of electricity technologies; a higher price of emissions triggers less investment in, and production of, fossil fuel-based electricity, thereby paving the way for zero-emission technologies. For the end-user sectors, emissions reductions require higher end-user prices, which are achieved by imposing a price on emissions.

In LIBEMOD, the 2030 GHG targets are reached by a common ETS quota system and an EU-wide uniform carbon tax in the non-ETS sectors. Next, the 2030 EU-wide target of a 32% share of renewables in final energy consumption is reached through an EU-wide renewable subsidy offered to all producers of renewable electricity.[2] Furthermore, the 2030 EU-wide energy efficiency target of a 32.5% improvement relative to the business-as-usual level in 2005 is reached through imposing an EU-wide tax on all types of energy being consumed by end users. To quantify the energy efficiency target and its implication for energy consumption in LIBEMOD, calculations in [3] are drawn upon. Finally, in LIBEMOD the EU 2050 policy target of a 95% emissions reduction in the electricity sector is implemented through an EU-wide emission price on all electricity producers.

3.3. The energy system model TIMES-Europe

TIMES-Europe is generated by the TIMES modelling framework [33], which is widely used to develop long-term bottom-up investment models of local, national, international or global energy systems, see [34]. It provides a detailed techno-economic description of resources, energy carriers, conversion technologies and energy demand. The model minimizes the total discounted cost of the energy system, subject to i) country-specific demand for energy services, and ii) an upper limit on CO_2 emissions from the entire electricity generation sector. The energy system cost includes a) investment expenditures in supply technologies, storage technologies, and international transmission lines, b) operating costs, and c) costs of net electricity imports.

TIMES-Europe is based on a TIMES model of the Scandinavian

[1] In LIBEMOD, there is only one type of environmental cost, namely the price of CO_2 emissions, which could be interpreted as the social cost of carbon for Europe. The model does not cover other types of indirect effects (i.e., externalities), like health damages and technology spillovers.

[2] The share of renewables in final energy demand is defined as i) the sum of renewable electricity generation and total end use of bioenergy (transformed to TWh) relative to ii) total consumption of electricity (less the electricity used in pumped storage hydro) and total consumption of primary energy among end users (transformed to TWh).

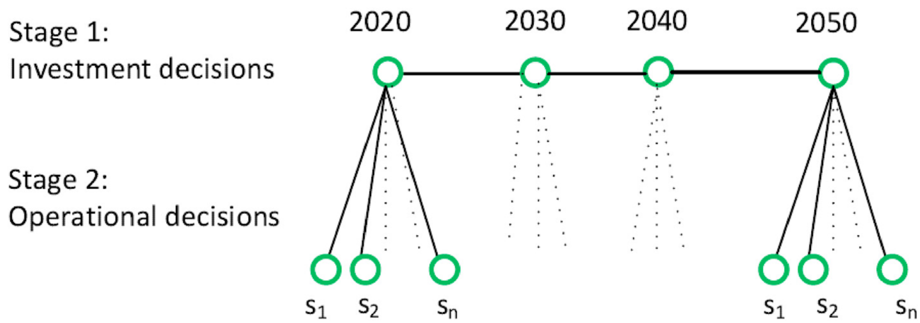

Fig. 1. The information structure of a two-stage stochastic model with short-term uncertainty.

energy system, see [35]. For the current study, the model has been extended to cover the power and district heat sectors of 29 interconnected European countries (EU-28 minus Cyprus, plus Norway and Switzerland). The model provides endogenous investment and operation for 2020, 2030, 2040 and 2050 (each year represents a period of 10 years) under uncertainty with respect to future demand and technology development.

The model includes numerous investment options, like nuclear; conventional power stations (thermal power plants combusting either coal, natural gas or oil, thereby emitting CO_2); renewable generation capacity (including reservoir hydro, run-of-river hydro, pumped storage hydro, bio power, onshore wind power, offshore wind power, solar PV, and centralized solar production); hydrogen production; energy storage (electric batteries and hydrogen); and international transmission between pairs of countries.

Each of the four model periods is divided into four seasons, each with a representative day with 12 2-h periods (48 time slices during a year). For each representative day in a season, it is required that the amount of charged electricity into the electric battery package of a country is greater than or equal to the amount of discharged electricity from the battery. Also, the stock of battery capacity develops over time, i.e., from one model year to the next, according to investment in this energy storage technology. In the model, there are different types of batteries available; some are designed primarily to store large amount of electricity, whereas others are used primarily to charge or discharge a large amount of electricity during a short period of time.

In TIMES-Europe, the capacities for the base year are calibrated by using 2015 statistics and are primarily based on data for ENTSO-E, see [36]. All values are measured in $euro_{2015}$.

3.3.1. Stochastic modelling approach

A two-stage stochastic framework, see [37], is applied to provide investment decisions in TIMES-Europe that explicitly considers various operational situations that can occur due to short-term uncertainty in offshore and onshore wind power generation, solar PV production and the load. The short-term uncertainty is modelled as three uncertain parameters representing the hourly capacity utilization rate for offshore wind power, onshore wind power, and solar PV and one uncertain parameter representing the hourly load.[3] Each of the four uncertain parameters can take 15 alternative values. A set of values for the four parameters is termed a scenario, referred to as *s1* to *s15* in Fig. 1.

The first-stage decisions—investment decisions in a model year (2020, 2030, 2040 or 2050)—are made under uncertainty, that is, *without* knowing the parameters of intermittent electricity generation and load for the year considered. The second-stage decisions—operational decisions for each of the 48 time slices in a model year—are made *after* the realisation of the uncertain parameters are revealed.

In each model year, each country determines its operational decisions for each of the 48 time slices, and for each time slice, there are 15 possible values for each of the four uncertain parameters. Only one scenario will materialize for each time slice, thereby revealing the value of the four parameters.

In our framework, operational decisions in each season within a model year are assumed independent of each other. Therefore, two interpretations are valid. First, the actors learn in the beginning of each season which of the 15 scenarios that has materialized for each of the 12 time slices in this season (hence actors learn four times during each model year). Second, the actors learn in the beginning of a model year which of the 15 scenarios that has materialized for each of the 48 times slices during the model year (hence actors learn only once during a model year).

The model solves all investment and operational decisions of all periods simultaneously by minimizing the sum of investment costs and expected operational costs, taking into account the capacities in the previous period. A multi-horizon framework that assumes no dependency of the operational decisions between the model years is used, see [38]. Also, similar to most investment models of the energy system, no forecast error of renewable generation and electricity demand is assumed. This may underestimate the need for flexibility. Still, with our approach a number of possible scenarios are considered at the time of investment. In contrast, with a deterministic model only *one* operational situation is considered.[4]

3.3.2. Scenario generation method

Historical hourly electricity consumption data from 2010 to 2015 from ENTSO-E, see [36], and the satellite-based performance database for renewable generation [39] are used to derive the 15 stochastic scenarios that represent the possible realizations of the uncertain parameters of onshore and offshore wind conditions, solar radiation and load.

To generate the stochastic scenarios, an iterative sampling methodology that was introduced in [40] is used. It combines the

[3] The hourly capacity utilization rates is defined as hourly electricity generation relative to maximal generation, where the latter is obtained if the installed capacity is fully utilized throughout the hour considered.

[4] Our stochastic model is equivalent to a deterministic model where each season consists of 15 representative days. This follows from (i) the fact that by construction, the probability that any scenario will materialize is 1/15, see Section 3.3.2, and (ii) the modelling of batteries where the net amount of electricity charged into the battery during any day is zero. With our requirement of (de facto) zero net charge into the battery during any representative day, the sequence of representative days in a season is of no importance in the "alternative deterministic model". Also, it is not necessary to specify an initial amount of electricity in the battery package (nor to specify how the initial amount of electricity evolves over seasons).

principles of random sampling and moment matching. This methodology has been used in several papers, for example, in [13] to study decarbonization strategies of the Arctic settlement at Svalbard, and in [35] to addresses the impact of zero energy buildings on the Scandinavian energy system towards 2050. In short, it involves repetitive random sampling of several historical days, in this paper 15 days, for each season and each country and selects the set of days that has the best statistical match with the historical data, measured by the first four moments.

In this study, the scenarios have been constructed under the requirement that the probability that a scenario *s* will materialize is equal for all scenarios. Note that no seasonal dependence of the parameters is assumed. For each country and each time slice, a set of parameters is generated for each scenario. Applying these in TIMES-Europe ensures that (i) the correlation between parameters, (ii) the correlation between European countries, and (iii) time dependencies reflect the raw data in a consistent way.

3.4. Soft-linking of equilibrium and energy system models

The primary goal of linking LIBEMOD and TIMES-Europe is to improve the decision support provided by these models. First, LIBEMOD is run subject to achieve the 2030 EU policy goals on emissions, renewables and energy efficiency. Next, LIBEMOD is run subject to achieve the 2050 EU target for emissions. For each model run, LIBEMOD provides model inputs to TIMES-Europe for annual electricity demand by country, user prices of fuels (which includes the model-determined price for CO_2 emissions), nuclear capacities (projections from the World Nuclear Association, see [41]), and the upper limit on CO_2 emissions that was imposed to represent the climate target.

Third, the annual electricity demand from LIBEMOD, along with data on hourly load from ENTSO-E, see [36], are used to construct 15 alternative load curves for a representative day for each season and each country. Fourth, TIMES-Europe is run to solve all investment and operational decisions of all periods simultaneously, subject to that for each time slice, there are 15 stochastic scenarios representing uncertain hourly load and uncertain capacity utilization rates for offshore wind power, onshore wind power, and solar. For each model year, TIMES-Europe imposes the user prices of fossil fuels, the nuclear capacities, and the upper limit on CO_2 emissions from the LIBEMOD model run.

Finally, to explore the importance of policy targets, LIBEMOD is run for 2030 and 2050 without imposing any policy targets. The output from these model runs, and the associated levels of CO_2 emissions that were generated, are used as inputs to TIMES-Europe in the same way as above.

4. Model cases

This section presents the combinations of policy targets and parameter assumptions that are used to address the research questions in this paper, henceforth referred to as model cases. Table 1 lists the 14 model cases. For model cases 1–13, the analysis distinguishes between two set of policy targets; the case of EU targets for 2030 and 2050, henceforth termed “Green”, and the case of no EU policy targets, henceforth referred to as “No target”. Finally, model case 14 studies the case of climate neutrality in the EU by 2040, see discussion below.

For parameter assumptions, this study distinguishes between various rates of technology learning in batteries, in PV technology, and in the offshore wind technology (low or high learning rate, as opposed to a medium learning rate—the reference value); whether the European electricity transmission grid can be expanded or not; and degree of demand variability (low or high variability, as opposed to medium variability—the reference value). Finally, in addition to the stochastic version of the TIMES-Europe model, also a deterministic version of this model is used. Whereas model cases represent long-term characteristics of technology costs, transmission grid expansion and electricity demand variability, the stochastic scenarios describe the short-term uncertainty of electricity supply and demand.

In the supplementary materials, cost development of batteries is described in part I, part II describes offshore wind power, onshore wind power and solar PV cost development, whereas part III contains information on transmission grid expansion.

4.1. Policy targets

This paper mainly distinguishes between two sets of policy targets: green and no target. Green contains two policy goals for GHG emissions (one for 2030 and another for 2050), one policy goal for energy efficiency, and one policy goal for renewables, see Table 2. In contrast, there is per construction no policy goal under “no target”. Note that the Green policy targets “lower emissions” and “improved energy efficiency” are accomplished by instruments that reduce demand for electricity. Hence, total demand for electricity is higher under No target than under Green.

Model cases 1–13 build on demand inputs from LIBEMOD. By construction, policy instruments do not trigger electrification in end-user sectors in LIBEMOD. Whereas this is a weakness of the model, the importance of an even more radical emission reduction than Green is tested by using demand for electricity by country from the scenario Directed Transition in [42]. This scenario assumes significant intertemporal policy steering through economic incentives and technology-specific support schemes to decarbonize the entire energy system by 2040, including (partial) electrification of end-user sectors. With such a radical target, demand for electricity in 2050 is 16% higher than in Green and 7% higher than in No Target.

4.2. Electricity demand variability

In model cases 1 to 11, it is assumed that the historical pattern of hourly electricity demand over a year will remain unchanged until 2050. However, this pattern may change in the future for two reasons. First, the government may want to use demand-side management to reduce the mismatch between demand for, and supply, of electricity; increased intermittent production tends to enhance this mismatch. This can be done, for example, by increasing the price of electricity faced by consumers when intermittent supply is low, and similarly decrease the consumer price of electricity when intermittent supply is high. Because weather conditions that affect intermittent supply have small effect on demand, such a policy will on average reduce demand variability. In model case 12, the partial effect of lower demand variability is studied.

Second, various policy instruments directed at lower CO_2 emissions in the end-user sectors transportation, the manufacturing industry and private and public heating/cooling may, over time, trigger electrification. This will not only increase demand for electricity, but also increase demand variability. In model case 13, the partial effect of higher demand variability is examined, whereas in model case 14 the joint effect of a higher demand variability and a higher demand for electricity is studied.

How can a change in demand variability be studied within our framework? In TIMES-Europe, demand in a country in each of the four seasons is modelled by a representative day with 12 2-h periods. Hence, over a year there are 48 periods; these are termed time slices. Let $D_{ref}(t,r)$ be the *share* of annual demand for

Table 1
Model cases—combinations of policy targets, model type and parameter assumptions.

Model case	Policy target	Model type	Parameter assumptions
1	Green	Stochastic	Reference case
2	Green	Deterministic	Reference case
3	No target	Stochastic	Reference case
4	No target	Deterministic	Reference case
5	Green	Stochastic	Low battery technology learning
6	Green	Stochastic	High battery technology learning
7	Green	Stochastic	Low PV technology learning
8	Green	Stochastic	High PV technology learning
9	Green	Stochastic	Low offshore wind technology learning
10	Green	Stochastic	High offshore wind technology learning
11	Green	Stochastic	Constrained transmission grid expansion
12	Green	Stochastic	Low electricity demand variability
13	Green	Stochastic	High electricity demand variability
14	Climate neutrality	Stochastic	Climate neutrality by 2040, high electricity demand variability

Table 2
Policy targets assumptions.

	No target	Green
Emission reductions	No target	40% reduction in GHG emissions by 2030 relative to 1990 levels, and 95% cuts in emissions in the power sector by 2050
Energy efficiency	No target	32.5% improved energy efficiency in 2030 (reflected in electricity demand from LIBEMOD)
Renewables target	No target	At least 32% renewable share in final energy by 2030 (reflected in electricity demand from LIBEMOD)

electricity in time slice t, $t = 1, 2, ..., 48$, in country r in the reference case. To study the *partial* impact of a change in demand variability, annual consumption is kept unchanged but demand in each time slice is adjusted so that demand variability over the year either decreases, see $D_{low}(t,r)$ below, or increases, see $D_{high}(t,r)$ below:

$$D_{low}(t,r) = \frac{\sqrt{D_{ref}(t,r)}}{\sum_{t=1}^{48}\sqrt{D_{ref}(t,r)}}$$

$$D_{high}(t,r) = \frac{D_{ref}(t,r)^2}{\sum_{t=1}^{48} D_{ref}(t,r)^2}$$

Fig. 2 shows the resulting pattern of electricity demand for Spain in 2050. By construction, in the low variability case maximum demand in a time slice during the year is lower than in the reference case while minimum demand in a time slice is higher than in the reference case. In contrast, in the high variability case the hourly demand profile is wider than in the reference case. In model case 12, the partial effect of a lower demand variability than in the reference case (model case 1) is studied, whereas model case 13 examines the effect of a higher demand variability than in the reference case. Finally, model case 14 focuses on partial electrification, which, relative to the reference case, is the combined effect of a) a higher *demand* for electricity, and b) a higher demand variability.

5. Results and discussion

5.1. CO_2 emissions

This paper examines energy-related CO_2 emissions from the European electricity and district heat sector. With **No target** (model case 3), continued growth in the use of fossil fuels keeps CO_2 emissions high, see Fig. 3. Emissions peak around 1,300 Mt CO_2 in 2030 before slowly declining to just below 1,200 Mt CO_2 in 2050. Towards 2030, the use of coal, in particular, boosts emissions, whereas the decline after 2030 reflects technology improvements in climate-friendly energy. With **Green** (model case 1), energy-related CO_2 emissions show a steep and sustained decline, fully in line with the trajectory required to achieve the objectives of the 2030 EU climate and energy package and the EU 2050 climate ambitions. The large reduction in emissions from 2015 to 2020 is mainly due to fuel switch from coal to natural gas.

5.2. Installed capacity and electricity generation

Fig. 4 compares installed electricity generation capacity for the two model cases Green and No Targets. For both cases, production is almost tripled between 2015 and 2050. For **Green**, there is a huge growth in the use of renewable technologies, especially solar PV and onshore wind power. In terms of capacity, solar PV becomes the largest electricity technology in the EU by 2050 with an installed capacity of 1,200 GW. There is also a slight increase in installed capacity of offshore wind power and biomass power. Because of the climate targets in 2030 and 2050, fossil-fuel based technologies are gradually phased out.

The most significant difference between the two model cases is that the capacity of fossil fuel plants remains almost constant in **No target.** In 2050, this capacity is close to 400 GW, as opposed to 70 GW in Green. Another major difference is that the capacity of onshore wind power is close to 1,000 GW in **Green** compared to 575 GW in **No target**. The production capacity of renewables is just above 2,600 GW in **Green**, whereas this capacity is 400 GW lower in **No target**.[5]

Fig. 5 compares electricity generation for model cases 1 and 3. Because there are 15 scenarios for each of the 48 time slices in a model year, electricity production by technology will vary between the scenarios of the same time slice. We therefore report *expected* electricity production for each electricity technology in each model

[5] For readability, concentrating solar power is grouped together with solar PV in Figs. 4 and 5. In Green, the combination of the emission target for 2020 and the large, existing capacities in the data year 2015 makes it optimal for most countries not to increase total capacity from 2015 to 2020. For a few countries, there is investment in capacities in 2020 and the sum of these investments are slightly lower than total depreciation of the 2015 capacities (aggregated over all countries and technologies).

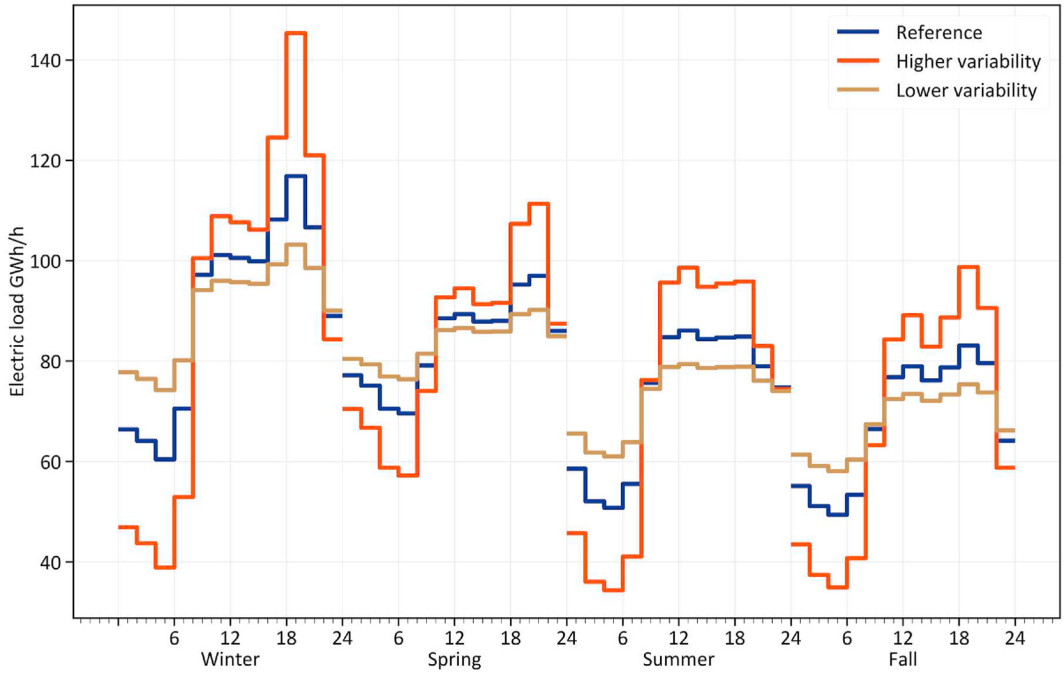

Fig. 2. Expected electricity demand profiles in 2050 for Spain for three electricity demand outcomes; Reference variability (based on historical data), Low variability (model case 12), and High variability (model case 13).

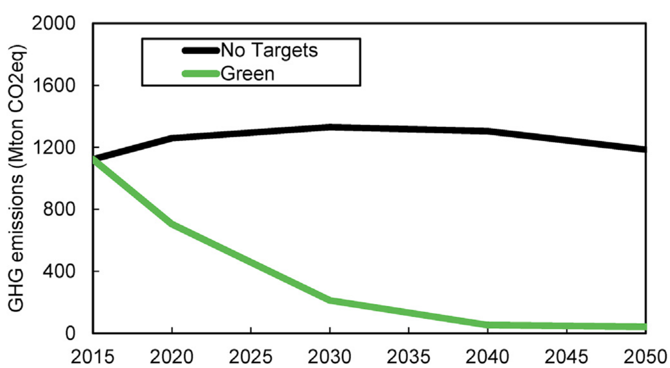

Fig. 3. CO_2 emissions by policy target assumption.

year, i.e., expected electricity production for each electricity technology in each time slice, aggregated over all time slices in a model year.

Whereas total capacity is almost at the same level in 2050 in these two model cases, see discussion above, expected total electricity generation is higher under No Target than under Green because of higher electricity demand under No target. With **No target**, coal power has a dominant position until 2040, when it peaks close to 1,500 TWh. In 2050, solar PV becomes the most important source of electricity with an annual production just above 1,600 TWh. For **Green**, electricity produced from coal is nearly phased out by 2030, whereas natural gas is phased out by 2040. Onshore wind power becomes the most important source of electricity in 2050, with expected production close to 2,200 TWh.

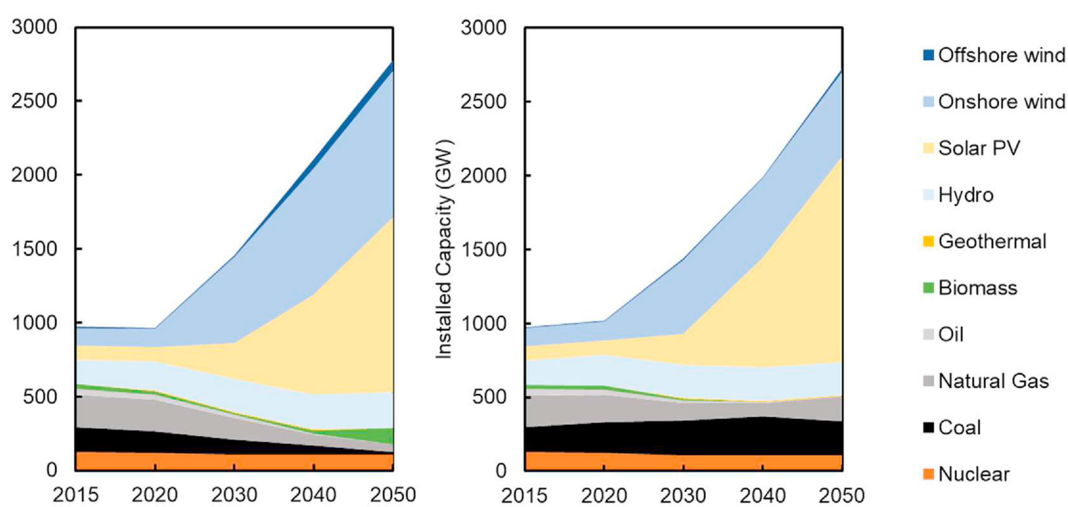

Fig. 4. Installed electricity generation capacity for the model cases Green (left) and No target (right).

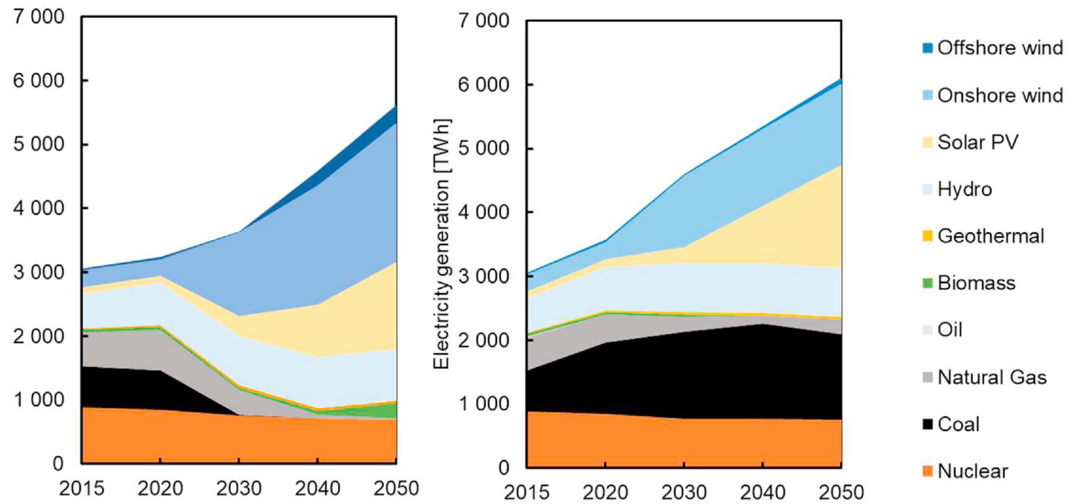

Fig. 5. Expected electricity generation in the model cases Green (left) and No target (right).

This is followed by (expected) production from solar PV, which reaches 1,400 TWh in 2050. For a comparison of our results for 2030 and 2050 with other studies, see the supplementary materials, part IV.

5.3. Flexibility requirements

We now turn to different types of flexibility: generation, transmission and storage. In TIMES-Europe, hydropower is divided into four groups: three cost classes for hydropower plants with reservoirs and one cost class for run-of-river hydropower. Furthermore, all new coal-fired power plants are of the advanced type, with units that can be operated in a load-following mode.

Panel A in Fig. 6 reveals that for **Green**, hydropower is the main provider of flexible electricity supply, followed by biomass. For **No target**, coal power and hydropower contribute equally as flexibility providers, followed by natural gas power.

In addition to flexible generation, additional sources of flexibility can help the integration of large shares of intermittent renewables in the future European power system. Expanding and upgrading grids can reduce congestion and increase the possibility of transferring electricity to places where it is needed. Consequently, significant investments in the European transmission grid are seen in Fig. 6, Panel B. For **No target**, more than a doubling of the total interconnection capacity (relative to 2015) is reached in 2050, whereas the grid capacity is five times higher in 2050 (than in 2015) for **Green**. Though the interconnection capacity is by construction the same for all of the 15 scenarios, actual power trade varies from scenario to scenario. For a discussion on how power trade varies between model cases 1 and 3, see the supplementary materials, part V.

As seen in Fig. 6, Panel A and B, power plants and grids are the two main sources of flexibility for model cases 1 and 3. However, energy storage will also be an important source of flexibility. Panel C in Fig. 6 shows the discharge capacity of lithium-ion batteries. Total battery discharge capacity is higher for **No target** than for **Green** (326 GW vs 198 GW). This is because there is considerably more electricity trade (reflecting higher transmission capacity) in **Green** than in **No target**. Two types of batteries are installed in both cases; one with an energy/power ratio of 4 kWh/kW and one with 1 kWh/kW. The latter technology has the highest capacity, see Panel C in Fig. 6.

5.4. Sensitivity analyses

As described in Table 1 in section 4, 14 model cases are analysed,

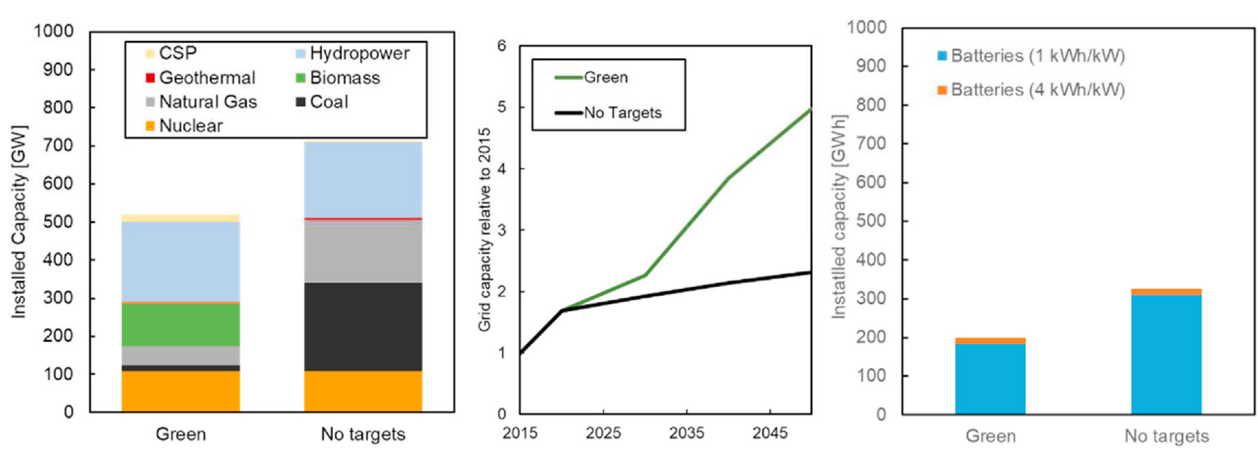

Fig. 6. Sources of flexibility. Panel A shows installed capacity of baseload and flexible generation in 2050. Panel B shows the development of the transmission grid relative to 2015, and Panel C shows storage discharge capacity of batteries in 2050.

ten of which are sensitivities of the green policy model case. Additionally, two deterministic cases and one stochastic case of climate neutrality are analysed. A summary of some of the key results from all model cases are described in Table 3, including grid capacity (in 2030 and 2050) relative to 2015, battery storage capacity in 2050 and market share of intermittent power in 2050. The latter is defined as the sum of production from solar PV, onshore and offshore wind power, divided by total electricity production. The green policy targets (defined in Table 2) can be obtained at an intermittent power share ranging from 65% to 70%. For these cases, battery capacity ranges from 80 to 351 GWh, and grid capacity in 2050 relative to grid capacity in 2015 varies from 4.3 to 6 (excluding model case 11).

As seen in Table 3, the deterministic model run with **Green** (model case 2) has 24% lower transmission grid capacity than the model run with the stochastic model (model case 1) in 2050, whereas for battery capacity the corresponding number is 41%. This means that the need for flexibility is underestimated in the deterministic model. Also under **No target**, battery storage capacity is lowest in the deterministic case (model case 3 vs. model case 4), but now transmission grid expansion is highest when the deterministic model is used. Both under **Green** and **No target**, the intermittent power share is highest in the deterministic case. This is similar to the results in [40].

As illustrated in Fig. 7, with default assumptions in **Green**, PV contributes 24% of the total electricity generation in 2050. With a high solar PV technology learning rate (see Table S4 in Supplementary materials for a definition of solar learning rates), this share is increased to more than 30% in 2050, whereas it is reduced to 9% with a low solar PV technology learning rate. As seen in the left panel in Fig. 7, a change in the cost of solar production mainly affects the market shares of solar PV and onshore wind power. If solar PV becomes cheaper, it captures a higher market share. Then it is not necessary with heavy investment in the expensive offshore wind power technology to meet the imposed CO_2 emissions constraint. Furthermore, whereas the cost of solar PV is important for the system composition, the impact on total system cost is moderate. With a high technology learning rate for solar PV, the total system cost decreases by 3% (see right scale in the left panel in Fig. 7). In this case, the investment cost for solar PV in 2050 is approximately 10% lower than in the reference case. Note, however, that R&D costs to ensure lower investment costs for solar PV are not included in the model. With a low technology learning rate for solar PV, the investment cost of solar PV is almost 20% higher than in the reference case, but the total system cost only increases by 2%.

With a high technology learning rate for *offshore wind power* (see right panel in Fig. 7), the market share for offshore wind power increases from 5% to 19% even though the reduction in investment cost is only 2.5% in 2050 (see Table S2 in Supplementary materials for a definition of offshore wind power learning rates). Furthermore, there is a reduction in the market share of onshore wind power. With a low technology learning rate for offshore wind power, the investment cost is almost 50% higher than in the reference case, and the market share of offshore wind power is close to 0%.

Although not shown here, a high technology learning rate for batteries (see Table S1 in Supplementary materials for a definition of battery learning rates) leads to an increase in the share of electricity from solar PV from 23% to 25%, whereas a low technological learning rate leads to a solar PV share of 21%. At the same time, the share of offshore wind power changes, but in the opposite direction. The impact on the total system cost is minor in both cases, with a decrease of 0.3% for a high technology learning rate (model case 6) and an increase of 0.2% for a low technology learning rate (model case 5).

Fig. 8 shows that the *shape of the hourly load curve* has a negligible impact on the composition of the future power system; this is the case both with a lower demand variability than in the reference case (the partial effect of demand management), and with a higher demand variability. However, with more demand variability total capacity of electricity technologies increases by 60 GW in 2050 (i.e., around 2%) relative to the reference case, and thus the system cost increases slightly. Whereas installed solar capacity increases by 83 GW (around 7%), there is a drop in installed capacity of offshore wind power, onshore wind power and bio power. To a large extent, the changes in capacity transform into changes in expected electricity production.

With partial electrification (model case 14), i.e., a higher demand for electricity combined with higher demand variability than in the reference case, there is substantial expansion of the transmission capacities, both in 2030 and 2050, whereas investment in batteries increases more moderately relative to the reference case (model case 1), see Table 3. The massive investment in transmission reflects that a higher demand for electricity has to be handled by more (renewable) intermittent power to meet the policy targets.

Table 3
Summary results from sensitivity analysis.

Model case	Policy target	Parameter assumptions	Grid capacity in 2030 relative to 2015	Grid capacity in 2050 relative to 2015	Battery storage capacity in 2050 (GWh)	Share of intermittent power in 2050
1	Green	Reference	2.3	5.1	198.5	0.68
2	Green	Reference	2.4	3.9	117.3	0.73
3	No target	Reference	1.7	2.0	326.1	0.49
4	No target	Reference	2.1	2.8	263.7	0.68
5	Green	Low battery technology learning	2.6	5.2	127.6	0.68
6	Green	High battery technology learning	2.5	5.0	271.5	0.68
7	Green	Low PV technology learning	2.7	6.0	80.3	0.65
8	Green	High PV technology learning	2.3	4.7	351.0	0.67
9	Green	Low offshore wind technology learning	2.6	5.5	201.4	0.67
10	Green	High offshore wind technology learning	2.5	4.3	173.2	0.69
11	Green	Constrained transmission grid expansion	1.6	1.6	308.5	0.69
12	Green	Low demand variability	2.6	5.2	215.6	0.70
13	Green	High demand variability	2.6	5.0	213.7	0.70
14	Climate neutrality	High demand and high demand variability	5.9	7.9	245.9	0.75

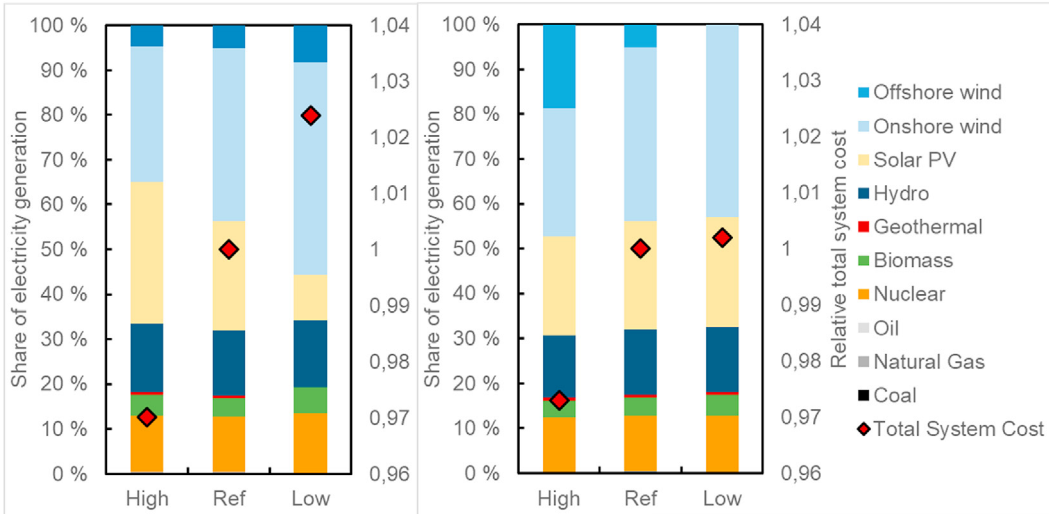

Fig. 7. High and low solar PV technology learning rate (left panel) and high and low offshore wind power technology learning rate (right panel) in 2050.

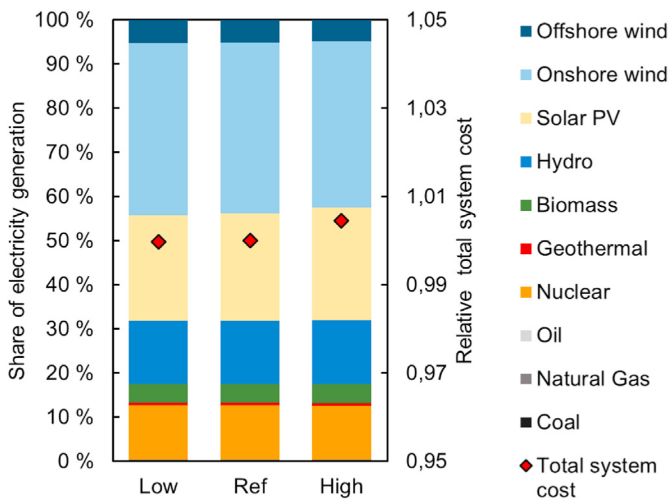

Fig. 8. Share of electricity generation, and impact on relative system cost, in 2050 for Low, Reference and High electricity demand variability.

Because solar and wind conditions vary across countries, it is optimal to concentrate intermittent investment in some countries and transport more power across Europe.

Table 3 provides more information on effects of changes in parameter values:

- With a low battery technology learning rate (i.e., lower than in the reference case), investment in batteries is (of course) lower than in the reference case, whereas the impact on grid investment is negligible.
- With a low offshore wind power technology learning rate, investments in both batteries and grid expansion are *higher* than in the reference case. A low offshore wind power technology learning rate decreases investment in offshore wind power, thereby paving the way for more investment in solar PV. Whereas solar PV has a very distinct hourly production profile, this is indeed not the case for wind power. Therefore, with more solar PV generation in all countries the need to store energy between time slices increases, which can be handled by investing more in both batteries and international grid capacity.
- With a low solar PV technology learning rate, investment in batteries is *lower* than in the reference case, whereas investment in grid expansion is *higher*. A low solar PV technology learning rate decreases investment in, and output from, solar PV significantly, thereby reducing the need to store energy between time slices over a day. With more expensive solar PV, the market share of wind power increases. Because wind conditions differ significantly between countries, the need for transmission capacity increases.
- With a low electricity demand variability, investments in batteries and grid expansion are hardly affected.

Fig. 9 shows battery capacity by country for **Green** (model case 1) and **Green with constrained transmission grid expansion** (model case 11). To control for country size, battery energy capacity (GWh) is measured relative to average hourly electricity demand (GWh), thereby making the ratio dimensionless. The darker the colour, the larger the ratio. In **Green** (left panel), a few countries have a relatively high ratio (Spain, Italy, Ireland and Lithuania), but there are also several countries with a low ratio or even a zero ratio (i.e., no capacity). For the model case **Green with constrained transmission grid expansion** (right panel), more countries invest in battery capacity: total battery capacity is almost 55% higher than in model case 1. The difference in total battery capacity between the two cases reflects that grid investment is preferred over investment in battery capacity.

Although total investment in batteries is higher in the model case without any expansion of the international transmission grid (model case 11) than in the reference case, in some countries investment in batteries is higher in the reference case than in model case 11. One example is Spain. Here, there is heavy investment in solar PV and wind power (in model case 1), in particular, in solar PV between 2040 and 2050. In order to utilize the additional power capacity, Spain expands the capacity of batteries and international transmission lines, thereby providing more flexibility.

To illustrate the stochastic nature of TIMES-Europe, the PV and offshore wind power production in UK in 2050 is taken as an example. Fig. 10 illustrates how power production varies between the 15 stochastic scenarios for **Green** (model case 1). In each diagram, the solid line represents the median of the scenarios. The coloured area represents all possible values for each individual time step, whereas the dark coloured area includes values between the

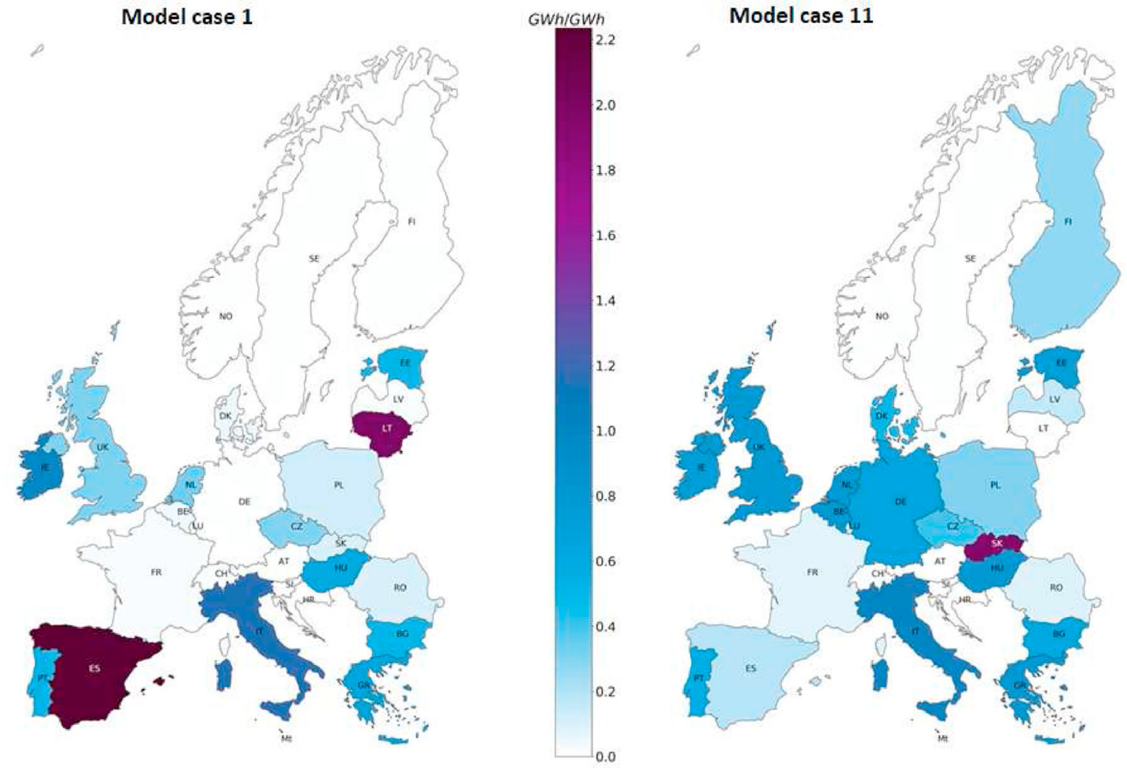

Fig. 9. Battery energy capacity per average hourly electricity demand in 2050 for the model countries. Left panel: Green (model case 1). Right panel: Green with constrained transmission grid expansion (model case 11).

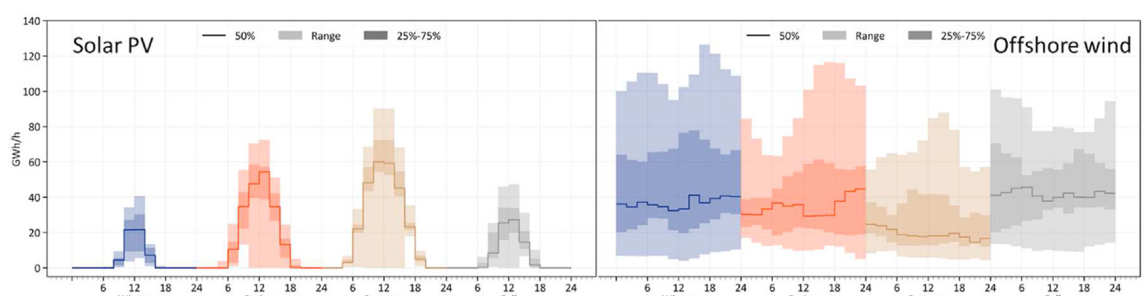

Fig. 10. Electricity generation from solar PV (left) and offshore wind power for the 15 stochastic scenarios in UK for Green (1) in 2050.

first and third quartile (50% of the values). As seen in Fig. 10, the solar PV generation follows a clear pattern, although there is variation from scenario to scenario. For offshore wind power production, the range of possible values is much larger than for PV, especially for winter, spring and fall.

6. Conclusions

A key challenge in modelling energy systems is to have both a sufficient detailed time resolution to mimic intermittent electricity supply and an adequate representation of technological properties and economic characteristics. In this paper, these concerns are handled by linking two models, LIBEMOD, a multimarket energy equilibrium model of Europe, and TIMES-Europe, a bottom-up stochastic model with a fine time resolution, to analyse the decarbonization of the electricity sector with consistent assumptions about future electricity demand and fuel prices.

The paper demonstrates the strength of using a stochastic modelling approach that considers the short-term uncertainty of intermittent supply and electricity demand to provide better decision support. It demonstrates that a deterministic model provides 24% lower grid capacity and 41% lower battery capacity in 2050 than the stochastic model and thus underestimates the need for flexibility. Furthermore, the deterministic approach overestimates the share of intermittent wind power, but underestimates the share of solar PV in the electricity generation mix.

The analysis shows that the European power sector can be decarbonized with a 65%–70% share of electricity supply from wind power and solar PV in 2050. The joint cost-optimal share of wind power and solar PV depends critically on technology development and grid expansion, whereas electricity demand variability is of less importance. The analysis shows that a higher technology learning rate for offshore wind power has a limited effect on solar PV investment. This is because a lower cost of offshore wind power primarily decreases the market share for onshore wind power, reflecting a high correlation between these two sources of supply.

This study provides support to the hypothesis that the EU energy and climate targets for 2030 and 2050 will increase the capacity of intermittent power, storage technologies and international transmission lines. In 2050, investment in electric battery capacity ranges from 80 GWh to 351 GWh. This type of investment is highly dependent on the learning rates for electric batteries and solar PV; the latter is due to the high variability of supply of solar over the day. Finally, the transmission grid capacity in 2050, measured relative to the capacity of 2015, ranges from 4.3 to 6.0. The expansion is primarily dependent on the technology learning rate of solar PV: to fully enjoy low PV costs, more transmission is required because solar conditions differ across European countries.

Credit author statement

Rolf Golombek: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Project administration. **Arne Lind**: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Project administration. **Hans-Kristian Ringkjøb**: Conceptualization, Methodology, Investigation, Writing – original draft. **Pernille Seljom**: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing.

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Data accessibility

Not relevant.

Declaration of competing interest

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

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Appendix A. Supplementary data

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