Energy 209 (2020) 118377

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

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

Hans-Kristian Ringkjøb [a, b, c, *], Peter M. Haugan [a], Pernille Seljom [b], Arne Lind [b], Fabian Wagner [c], Sennai Mesfun [c, d]

[a] Geophysical Institute, University of Bergen, Allégaten 70, 5007, Bergen, Norway
[b] Institute for Energy Technology (IFE), Instituttveien 18, 2007, Kjeller, Norway
[c] International Institute for Applied Systems Analysis (IIASA), Schlossplatz 1, A-2361, Laxenburg, Austria
[d] RISE Research Institutes of Sweden AB, P.O. Box 5604, 114 86, Stockholm, Sweden

ARTICLE INFO

Article history:
Received 22 December 2019
Received in revised form
1 July 2020
Accepted 11 July 2020
Available online 27 July 2020

Keywords:
Energy modelling
TIMES energy-Models
Variable renewable energy
Stochastic modelling

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, the 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 these findings, a stochastic approach is recommended for long-term studies of energy systems with large shares of variable renewable energy sources.

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]. Pfenninger et al. [5], point 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 [6]. For example, Haydt et al. [7] showed that low resolution models could overestimate the contribution from variable renewables (VRES) and underestimate CO_2 emissions. Similarly, Ludig et al. [8] found that having a too coarse representation of variability could lead to an underestimation of total system cost. 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.

* Corresponding author. Geophysical Institute, University of Bergen, Allégaten 70, 5007, Bergen, Norway.
E-mail address: hans-kristian.ringkjob@uib.no (H.-K. Ringkjøb).

https://doi.org/10.1016/j.energy.2020.118377
0360-5442/

1.1. Literature review

Improving the representation of short-term variations of solar and wind in long-term energy models have seen increased attention in recent years. Different methodologies have been proposed in the literature, some of which are presented in Table 1. For a more thorough review, see Collins et al. [9] who examined the challenges of long-term energy models when dealing with variable solar and wind, and state-of-the-art methodologies to address them.

One approach is to soft-link long-term energy models with operational power system models that treat the short-term operations of the grid in more detail. An example is the linking of the Dispa-SET unit commitment and dispatch model and the JRC EU-TIMES long-term energy model [17]. Another example is Welsch et al. [10], who 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. Moreover, Poncelet et al. [6], 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. 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 [18].

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 [19]. Kannan & Turton [20] increased the temporal resolution of a Swiss TIMES model from 8 (two diurnal time-slices per season) to 288 time-slices (24 h $\times$ 3 days x 4 seasons), achieving what they referred to as “a far better solution” in the more detailed model. TIMES-Norway [21] uses 260 times slices annually in order to give a detailed description of the Norwegian hydropower system.

Another recently active area of research has focused on the various methods to select representative days or time-slices. Pfenninger [22] 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. [14] 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. [23]. For example, Gaur et al. [24] added a unit commitment 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. Another approach is to incorporate modelling of operating reserves (ancillary services), as in Ref. [25].

Stochastic modelling has in recent years emerged as a way of representing short-term uncertainty in long-term energy models, and has for example been used to model solar and wind variability in an Arctic energy system [26]. While traditional deterministic models make investment decisions based on only one operational scenario, a stochastic model takes into account a range of representative operational scenarios that can occur (see section 2.4.3). Seljom and Tomasgard [27] 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. [28] 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 an underestimation of costs and flexibility requirements. EMPIRE is another example of a stochastic model of the European electricity system, used for example to study the role of demand response in Europe [29].

1.2. Hypothesis and contributions

This work evaluates and demonstrates 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, a least-cost optimisation model of the European power and district heat sectors, TIMES-Europe, was developed and applied. Five model versions have been developed, all fundamentally

Table 1
Studies focusing on the representation of short-term variability in energy models (Abbreviations: ESM = Energy system model, UC = Unit commitment, OSM = Operational system model, MILP = Mixed integer linear programming).

Model	Methodology	Temporal resolution	Geographical resolution	Ref
TIMES, LUSYM	Soft-linking of ESM and UC	12, 8760	Belgium	[6]
OSeMOSYS, TIMES, PLEXOS	Technical operational constraints & soft-linking of ESM and OSM	12, 8784	Ireland	[10]
LIMES	Increased temporal resolution	4, 8, 16, 48, 96	Germany	[8]
LIMES-EU+	Heuristics	49	Europe + MENA	[11]
LIMES-EU	Clustering + increased temporal resolution	8 to 800	Europe	[12]
Calliope	Resampling, clustering, heuristics	144 to 8760	Great Britain	[13]
Calliope	Random sampling, clustering, individual years, “importance subsampling”	480, 1920, 8760	United Kingdom	[14]
TIMES	Stochastic modelling	48 (90 scenarios)	Denmark	[15]
n/a	Heuristics, clustering, random sampling, MILP optimisation, hybrid approach	2–24 days	Belgium	[16]

identical but each with increasing temporal resolution. 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. Belgium [6], Ireland [10], or Great Britain [14]. 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, this paper explicitly compares the performance of stochastic versus high-resolution deterministic modeling approaches using TIMES at the European level. This study is the first to assess how fine temporal resolution a deterministic model must have in order to perform approximately as well as a stochastic model. The main hypothesis in this work is that a stochastic modelling approach gives a more realistic representation of the electricity sector, especially when considering a system with a high share of electricity production from intermittent renewable energy sources. Hence, it will provide different investment strategies compared to a deterministic model with the same temporal resolution. Instead of just increasing the number of time slices in an energy system model, this work demonstrates how a stochastic approach can replicate and even improve upon a deterministic model with a considerably higher temporal resolution. In order to test the main hypothesis, a TIMES long-term energy system model is applied to a case-study of the European power and district heat systems towards 2050.

2. Data & Methods

The overarching methodology of this paper is presented in Fig. 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 Fig. 1 with a week of hourly data for Norway and further discussed in section 2.3. 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 using the stochastic model with 48 time-slices as a benchmark for comparison. 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.

2.1. 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 [30]. The model is based on a TIMES model of the Scandinavian energy system [15], 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 Fig. 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. A discount rate of 4% is used, 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.

2.2. 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 [32]. The electricity demand increases by 27% between 2015 and 2050 ($\sim$3000 TWh to $\sim$3800 TWh), whereas the district heat demand increases by 10% ($\sim$610 TWh to $\sim$670 TWh). Electrification of heating/cooling and an increased use of electric appliances in the residential and tertiary sectors are the main drivers of the increased electricity demand in the EU Reference Scenario [32]. Many studies have shown that e.g. electrification of the transport sector could lead to a steeper increase of electricity demand than what is assumed here [33]. For example, for a 100% renewable energy scenario both Greenpeace Energy [R]evolution [34] and Breyer et al. [35] see about a doubling of global electricity consumption towards 2050.

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 [36]. The CO_2 price in 2015 of 7.7 €/ton is based on [37], and assumed to increase to 55 €/ton in 2050 [36]. This is a conservative estimate in comparison to other similar studies. For example, Bogdanov et al. [38] assume a CO_2 price of 150 €/ton in 2050, and Zappa et al. [39] assume a CO2 price of 120 €/ton in 2050.

All other subsidies, taxes, and national climate goals are excluded. 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.

2.3. Input data

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) are used, spanning from 1985 to 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 [40].

The solar and wind data-sets are obtained from renewables.ninja, a web application based on the Global Solar Energy Estimator (GSEE) model [41] and the Virtual Wind Farm (VWF) model [42]. These models estimate hourly availability of solar and wind generation based on weather data from the MERRA reanalysis [43], and are bias-corrected for European countries using national

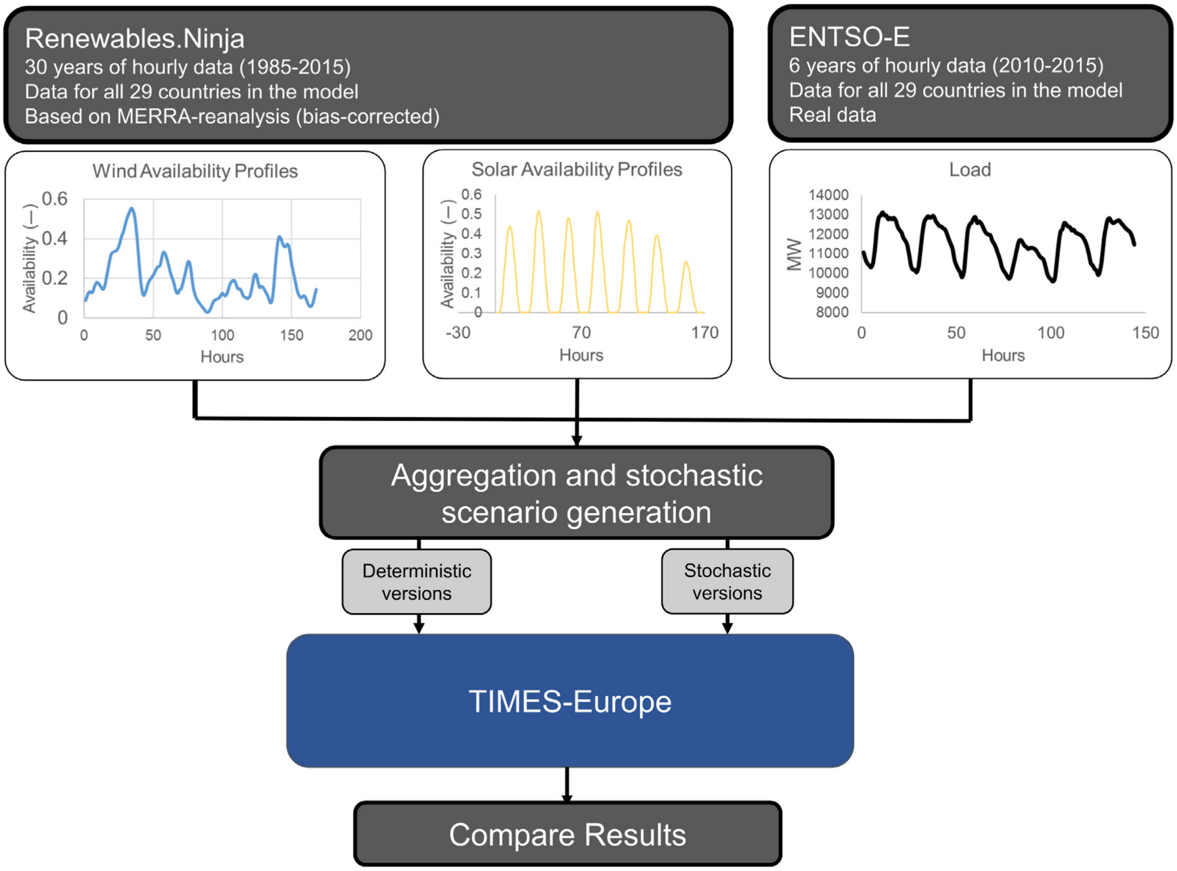

Fig. 1. Overarching methodology followed in this paper.

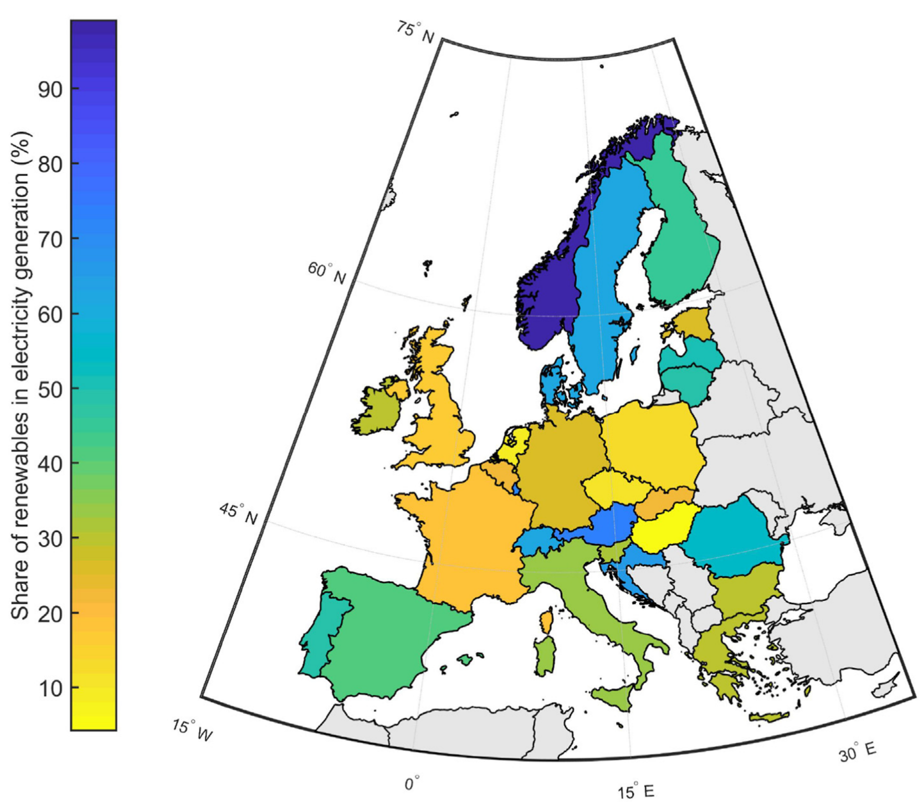

Fig. 2. Modelled countries and their share of renewables in the electricity generation mix in 2015 [31].

generation data.

The wind and solar data allows modelling the effect of solar and wind correlation across Europe in the 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. Figs. 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 [44]. 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 [45]. The district heat load profile, which describes the fluctuation of district heat demand within a year, is retrieved from the EnergyPlan model [46], 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 important for both power-to-heat technologies and 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 Tables 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 (based on [47] for EU countries, [48] for Norway and [49] for Switzerland), taking into account protected areas, mountainous areas etc.

2.4. Model versions

In order to explore the importance of the temporal resolution and modelling methodology in long-term energy models, several model versions were developed. Fundamentally, all versions work in the same way and with the same data, but with varying temporal resolution and modelling methodology. The following sections present the developed model versions.

2.4.1. Temporal resolution

Five model versions with respectively 12, 48, 192, 672 and 2016 time slices per year were developed (see description of time-slice division in Table 2). The number of time-slices in TIMES models usually range between 4 and 48 [24], with the most detailed models having 288 time-slices [19]. The 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.

2.4.2. 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.

2.4.3. Stochastic approach

A two-stage stochastic model [50] is applied 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. A stochastic model with only one operational scenario would be equivalent to a simplified deterministic model.

Fig. 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 [51], 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.

In the stochastic modelling approach, the generated scenarios describe the uncertainty of the solar and wind availability and in addition represent realistic operational situations [27]. The scenarios are generated through a method that combines random sampling and moment matching [27]. In short, the technique

Table 2
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 h), a day time-slice (07.00–23.00, 16 h) and a peak time-slice (1 h)
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)

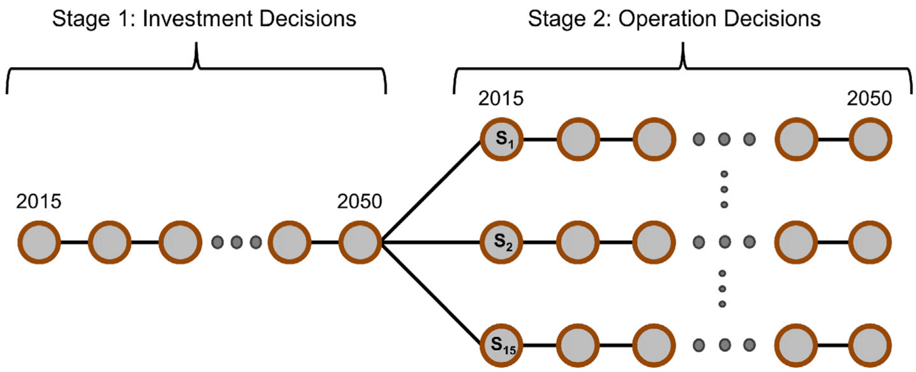

Fig. 3. Illustration of a two-stage stochastic model with fifteen operational scenarios (adapted from Ref. [15]).

Table 3
Model runs in this study.

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

involves randomly sampling a large set of historical days of the solar, wind and load data and then select the set of days that has the best fit with the statistical properties of the original datasets. A more detailed explanation of the procedure is provided in Ref. [26].

2.4.4. Model versions

Table 3 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. A model with 8760 time-slices was also developed, but was unsolvable due to RAM limitations. This also shows why it is important to reduce the temporal resolution in long-term energy-models to make them computationally tractable.

3. Results and discussion

In this section, results from the various model versions are compared, and the impact of increasing the temporal resolution or modelling with a stochastic modelling approach is assessed. 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, the energy system related results are investigated, looking at the features of a future European power system. Second, the computational performance of each model version is assessed, discussing the trade-off between model accuracy and computational effort. Finally, the implications of the work is discussed and topics to be explored for future studies are suggested.

3.1. Model performance

Fig. 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 Fig. 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* (~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 Fig. 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*.

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

[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.

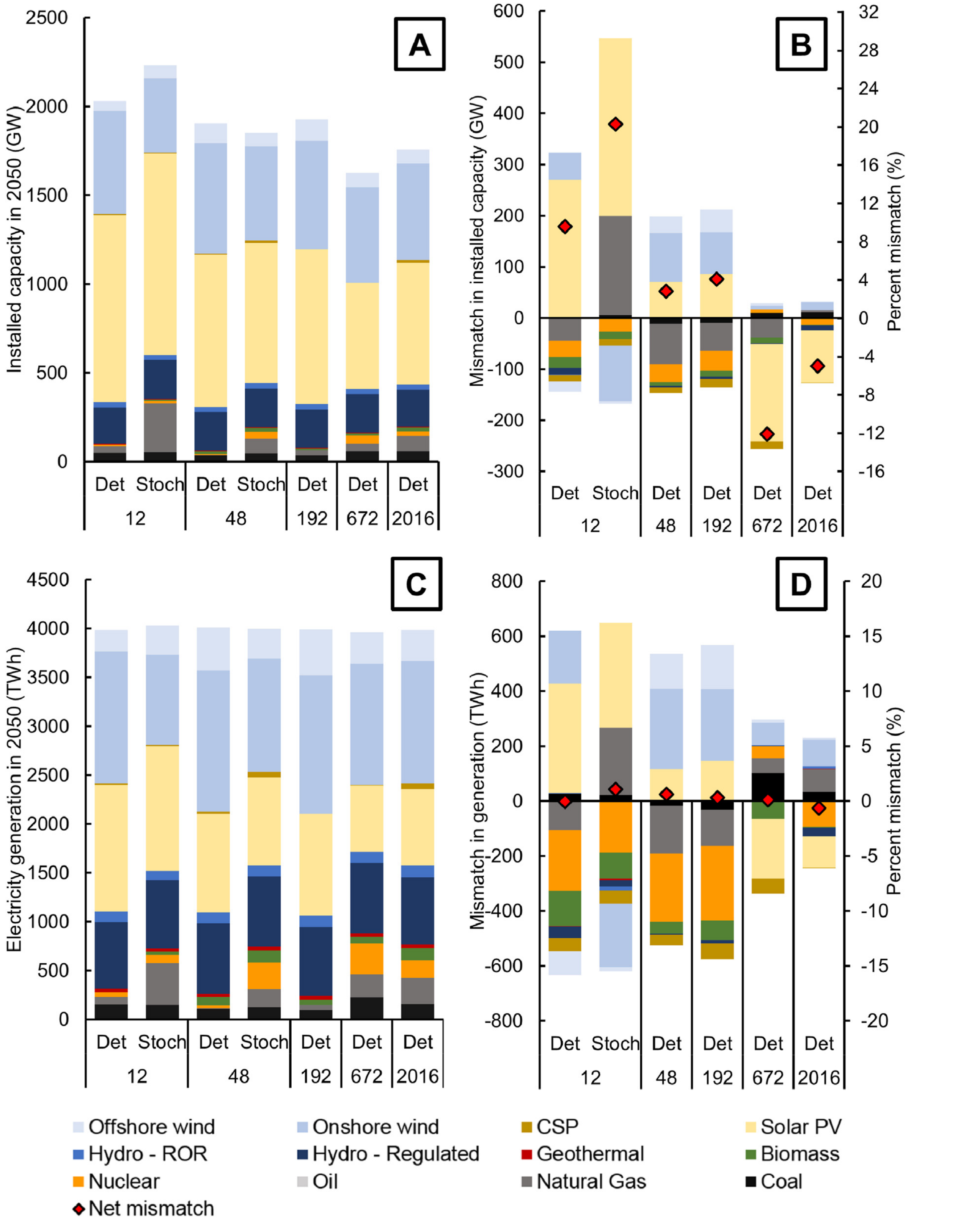

Fig. 4. European aggregated installed capacity and electricity generation in 2050 and associated mismatch between model versions: Panel A shows the installed capacity in 2050, whereas panel B shows the mismatch in installed capacity relative to the *Stoch48* model. Panel C shows the electricity generation 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.

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 Fig. 4 only shows the European aggregated results for 2050, Figs. 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*.

The transition to a power system based primarily on renewable energy sources also leads to major cuts in CO_2 emissions (see Fig. 5). 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.

Fig. 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.

3.1.1. 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

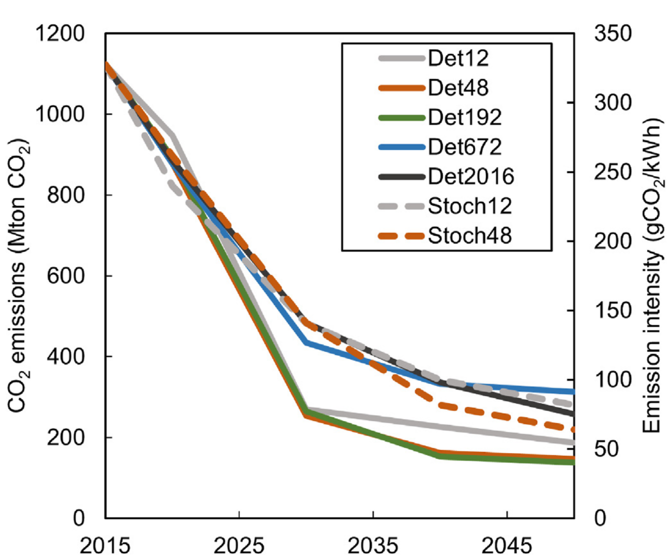

Fig. 5. Estimated CO_2 emissions from 2015 to 2050.

renewables to generate electricity when needed, systematically underestimating the need for flexible and base-load generation (Fig. 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 (Fig. 6 panel B), with more than a doubling of total interconnection capacity. Energy storage will also be an important source of flexibility. Fig. 6 panel C shows the energy storage discharge capacity in 2050 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. Including the transport sector could also greatly impact the need for grid-scale battery storage through the battery capacity in electric vehicles.

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), the resulting energy system configuration from *Det672* and *Det2016* can be exposed 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 [27,52]. The VSS works by fixing the investments from a deterministic model and then running the model with the stochastic operational scenarios. In other words, the investments from *Det672* and *Det2016* are implemented in *Stoch48*, and then run 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 [15]. The deterministic models have been tested using 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.

3.1.2. Costs of a highly renewable European power system

Fig. 7 shows the aggregated annual costs for the European

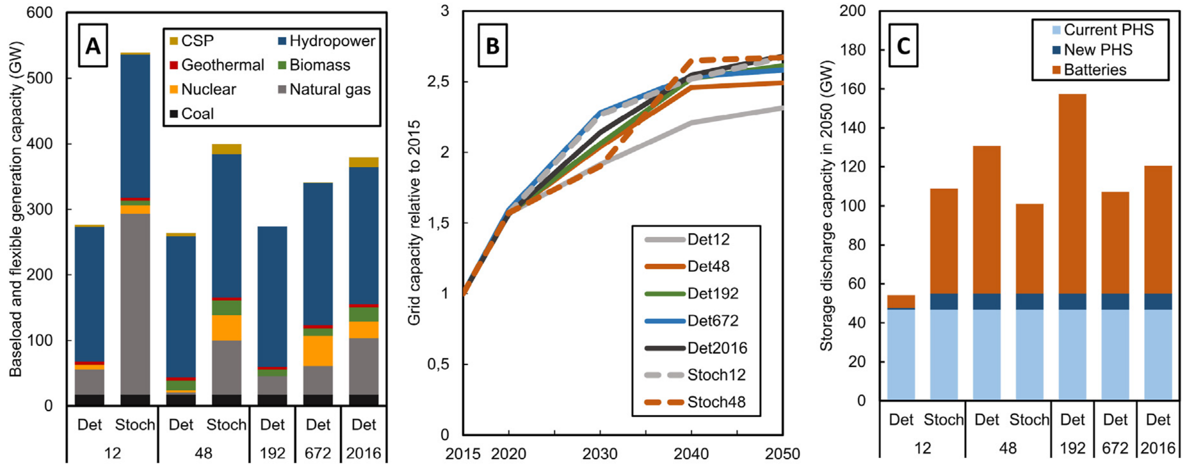

Fig. 6. Sources of flexibility: A) shows the installed capacity of baseload and flexible generation in 2050, B) shows the development of the transmission grid relative to 2015, and C) shows storage discharge capacity in 2050.

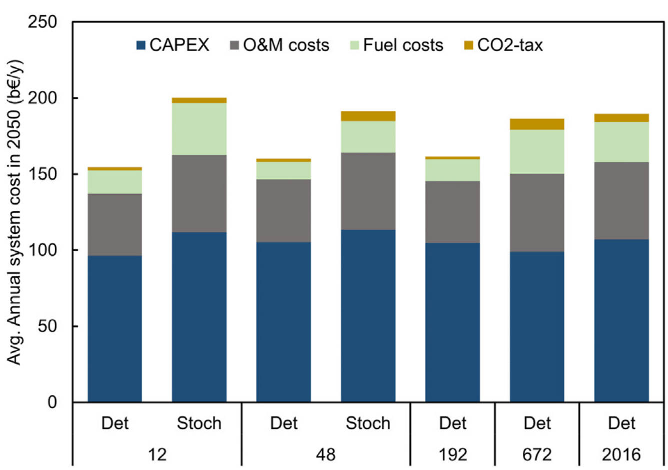

Fig. 7. Average annual system costs in 2050.

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 to 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 3.1.1).

The maps in Fig. 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 Fig. 8 return lower shadow prices in 2050 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 and 58.7 €/MWh, corresponding to a deviation of 4–6%.

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 Fig. 9 and Table 4). 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 10 h.

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

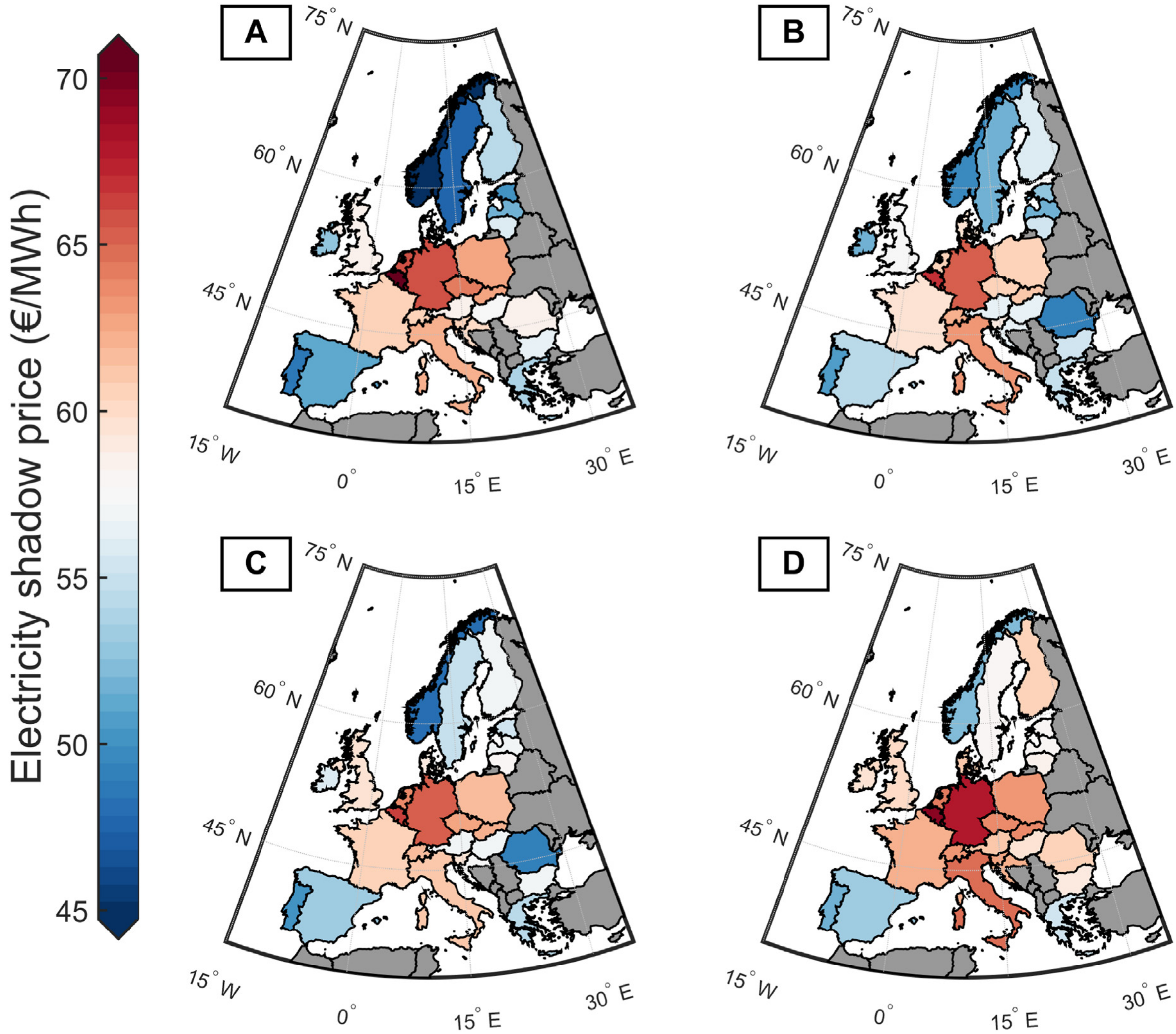

Fig. 8. Average electricity shadow prices by country in 2050 for A) *Det48*, B) *Det672*, C) *Det2016*, and D) *Stoch48*.

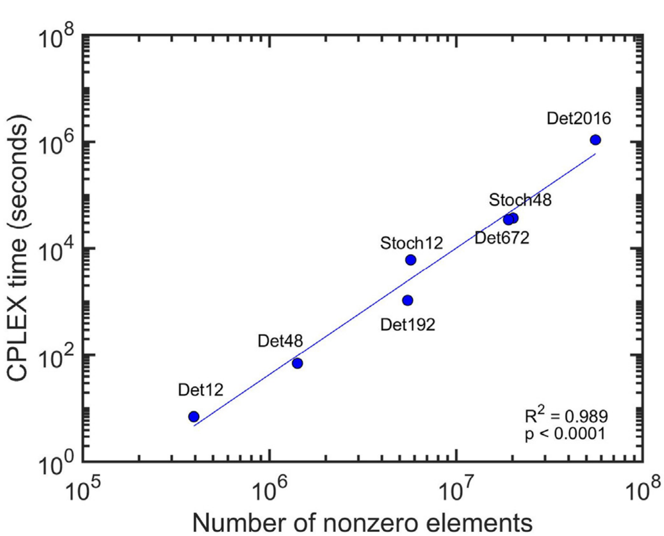

Fig. 9. CPLEX time in seconds relative to number of nonzero elements (note the logarithmic axes).

modelling approach is able to weigh up for its lower temporal resolution.

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. A conventional deterministic approach was compared to a stochastic approach, and the effect of increasing the temporal resolution was also assessed. In addition, the introduction of a heuristic that limits the contribution of VRES has been discussed, and how it can improve the output from low resolution deterministic models. This paper does not, however, compare 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 low resolution 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-

Table 4
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

processing, which is a drawback of the stochastic model version used in this paper. It is also important to mention that deterministic models with hourly temporal resolution exist, including e.g. EnergyPlan [53] and the LUT Energy Transition Model [54]. The former follows a simulation based approach, which could be an alternative to the optimisation based models discussed in this paper [55]. Another alternative 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 [56]. This assessment on a national scale could therefore underestimate necessary investment in the distribution grid, even though 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 [57]. 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 [29]. 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 [58]. Connolly et al. [59] modelled a 100% renewable energy system in Europe by 2050 for all sectors. They found that such a system is technically feasible, helped by the extra flexibility gained by additional sector coupling. The model EnergyPlan was used, having hourly resolution but with the EU modelled as one single region. For future research, the model and approach followed in this study could be expanded to encompass all sectors. One could then further examine the synergies of sector coupling, both in terms of extra flexibility in the power system and also how this could enable renewable energy sources to decarbonise more difficult sectors such as transportation or industry. In addition, the results lead to a VRES share of about 60% of the electricity generation, with a total renewable share of about 85%. 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, the representation of solar and wind variability in a TIMES long-term energy model of the European power and district heat sectors towards 2050 is assessed.

This paper has 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.

This 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 system model to investigate such aspects, including sector coupling and 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.

Credit author statement

Hans-Kristian Ringkjøb: Conceptualisation, Data Curation, Software, Methodology, Formal Analysis, Visualisation, Writing – Original Draft. **Peter Haugan:** Conceptualisation, Writing - Review & Editing, Supervision. **Pernille Seljom:** Conceptualisation, Methodology, Writing - Review & Editing. **Arne Lind:** Conceptualisation, Resources, Writing – Review & Editing, Supervision. **Fabian Wagner:** Conceptualisation, Writing – Review & Editing, Supervision. **Sennai Mesfun:** Conceptualisation, Writing – Review & Editing.

Declaration of competing interest

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

5. Acknowledgements

The first author's research project is financed by the University of Bergen. Part of the research was developed during the Young Scientists Summer Program at the International Institute for Systems Analysis (IIASA), with financial support from the Research Council of Norway.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2020.118377.

References

[1] European Commission. A Clean Planet for all. A European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy - communication from the Commission to the European Parliament, the Council, the European and Social Committee and the Committe. Tech. rep.,European Commission; 2018. https://ec.europa.eu/clima/policies/strategies/2050_en.

[2] Vartiainen E, Masson G, Breyer C, Moser D, Román Medina E. Impact of weighted average cost of capital, capital expenditure, and other parameters on future utility-scale PV levelised cost of electricity. Progress in photovoltaics: research and applications. 2019. p. 1–15. https://onlinelibrary.wiley.com/doi/abs/10.1002/pip.3189.

[3] Ueckerdt F, Brecha R, Luderer G. Analyzing major challenges of wind and solar variability in power systems. Renew Energy 2015;81:1–10. https://doi.org/10.1016/j.renene.2015.03.002.

[4] Ringkjøb HK, Haugan PM, Solbrekke IM. A review of modelling tools for energy and electricity systems with large shares of variable renewables. Renew Sustain Energy Rev 2018;96(August):440–59. https://doi.org/10.1016/j.rser.2018.08.002.

[5] Pfenninger S, Hawkes A, Keirstead J. Energy systems modeling for twenty-first century energy challenges. Renew Sustain Energy Rev 2014;33:74–86. https://doi.org/10.1016/j.rser.2014.02.003. https://linkinghub.elsevier.com/retrieve/pii/S1364032114000872.

[6] Poncelet K, Delarue E, Six D, Duerinck J, Dâ€™haeseleer W. Impact of the level of temporal and operational detail in energy-system planning models. Appl Energy 2016;162:631–43. https://doi.org/10.1016/j.apenergy.2015.10.100. https://linkinghub.elsevier.com/retrieve/pii/S0306261915013276.

[7] Haydt G, Leal V, Pina A, Silva CA. The relevance of the energy resource dynamics in the mid/long-term energy planning models. Renew Energy 2011;36(11):3068–74. https://doi.org/10.1016/j.renene.2011.03.028.

[8] Ludig S, Haller M, Schmid E, Bauer N. Fluctuating renewables in a long-term climate change mitigation strategy. Energy 2011;36(11):6674–85. https://doi.org/10.1016/j.energy.2011.08.021.

[9] Collins S, Deane JP, Poncelet K, Panos E, Pietzcker RC, Delarue E, Ó Gallachóir BP. Integrating short term variations of the power system into integrated energy system models: a methodological review. Renew Sustain Energy Rev 2017;76(January):839–56. https://doi.org/10.1016/j.rser.2017.03.090.

[10] Welsch M, Deane P, Howells M, Ó Gallachóir B, Rogan F, Bazilian M, Rogner H-H. Incorporating flexibility requirements into long-term energy system models â€" A case study on high levels of renewable electricity penetration in Ireland. Appl Energy 2014;135:600–15. https://doi.org/10.1016/j.apenergy.2014.08.072. https://linkinghub.elsevier.com/retrieve/pii/S0306261914008836.

[11] Haller M, Ludig S, Bauer N. Decarbonization scenarios for the EU and MENA power system: considering spatial distribution and short term dynamics of renewable generation. Energy Pol 2012;47:282–90. https://doi.org/10.1016/j.enpol.2012.04.069. https://linkinghub.elsevier.com/retrieve/pii/S0301421512003746.

[12] Nahmmacher P, Schmid E, Hirth L, Knopf B. Carpe diem: a novel approach to select representative days for long-term power system modeling. Energy 2016;112:430–42. https://doi.org/10.1016/j.energy.2016.06.081. https://linkinghub.elsevier.com/retrieve/pii/S0360544216308556.

[13] Pfenninger S, Keirstead J. Renewables, nuclear, or fossil fuels? Scenarios for Great Britain's power system considering costs, emissions and energy security. Appl Energy 2015;152:83–93. https://doi.org/10.1016/j.apenergy.2015.04.102. https://linkinghub.elsevier.com/retrieve/pii/S0306261915005656.

[14] Hilbers AP, Brayshaw DJ, Gandy A. Importance subsampling: improving power system planning under climate-based uncertainty. Appl Energy 2019;251(March):113114. https://doi.org/10.1016/j.apenergy.2019.04.110. https://linkinghub.elsevier.com/retrieve/pii/S0306261919307639.

[15] Seljom P, Lindberg KB, Tomasgard A, Doorman G, Sartori I. The impact of zero energy buildings on the scandinavian energy system. Energy 2017;118:284–96. https://doi.org/10.1016/j.energy.2016.12.008. https://linkinghub.elsevier.com/retrieve/pii/S0360544216318138.

[16] Poncelet K, Hoschle H, Delarue E, Virag A, Drhaeseleer W. Selecting representative days for capturing the implications of integrating intermittent renewables in generation expansion planning problems. IEEE Trans Power Syst 2017;32(3):1936–48. https://doi.org/10.1109/TPWRS.2016.2596803. http://ieeexplore.ieee.org/document/7527691/.

[17] Pavičević M, Mangipinto A, Nijs W, Lombardi F, Kavvadias K, Jiménez Navarro JP, Colombo E, Quoilin S. The potential of sector coupling in future European energy systems: soft linking between the Dispa-SET and JRC-EU-TIMES models. Appl Energy 2020;267(April):115100. https://doi.org/10.1016/j.apenergy.2020.115100.

[18] Helgesen PI, Lind A, Ivanova O, Tomasgard A. Using a hybrid hard-linked model to analyze reduced climate gas emissions from transport. Energy 2018;156:196–212. https://doi.org/10.1016/j.energy.2018.05.005. https://linkinghub.elsevier.com/retrieve/pii/S0360544218308247.

[19] Pina A, Silva C, Ferrão P. Modeling hourly electricity dynamics for policy making in long-term scenarios. Energy Pol 2011;39(9):4692–702. https://doi.org/10.1016/j.enpol.2011.06.062. https://linkinghub.elsevier.com/retrieve/pii/S0301421511005180.

[20] Kannan R, Turton H. A long-term electricity dispatch model with the TIMES framework. Environ Model Assess 2013;18(3):325–43. https://doi.org/10.1007/s10666-012-9346-y. http://link.springer.com/10.1007/s10666-012-9346-y.

[21] Lind A, Rosenberg E, Seljom P, Espegren K, Fidje A, Lindberg K. Analysis of the EU renewable energy directive by a techno-economic optimisation model. Energy Pol 2013;60(December 2008):364–77. https://doi.org/10.1016/j.enpol.2013.05.053. https://linkinghub.elsevier.com/retrieve/pii/S0301421513003893.

[22] Pfenninger S. Dealing with multiple decades of hourly wind and PV time series in energy models: a comparison of methods to reduce time resolution and the planning implications of inter-annual variability. Appl Energy 2017;197:1–13. https://doi.org/10.1016/j.apenergy.2017.03.051. https://linkinghub.elsevier.com/retrieve/pii/S0306261917302775.

[23] De Jonghe C, Delarue E, Belmans R, D'haeseleer W. Determining optimal electricity technology mix with high level of wind power penetration. Appl Energy 2011;88(6):2231–8. https://doi.org/10.1016/j.apenergy.2010.12.046. https://linkinghub.elsevier.com/retrieve/pii/S0306261910005660.

[24] Gaur AS, Das P, Jain A, Bhakar R, Mathur J. Long-term energy system planning considering short-term operational constraints. Energy Strategy Reviews 2019;26(June):100383. https://doi.org/10.1016/j.esr.2019.100383. https://linkinghub.elsevier.com/retrieve/pii/S2211467X19300768.

[25] Vögelin P, Georges G, Noembrini F, Koch B, Boulouchos K, Buffat R, Raubal M, Beccuti G, Demiray T, Panos E, Kannan R. System modelling for assessing the potential of decentralised biomass-CHP plants to stabilise the Swiss electricity network with increased fluctuating renewable generation. https://www.infothek-biomasse.ch/images//284_2016_Voegelin_system_modelling.pdf; 2016.

[26] Ringkjøb H-K, Haugan PM, Nybø A. Transitioning remote Arctic settlements to renewable energy systems A modelling study of Longyearbyen. Svalbard, Applied Energy 2020;258:114079. https://doi.org/10.1016/

j.apenergy.2019.114079. November 2019, https://linkinghub.elsevier.com/retrieve/pii/S0306261919317660.
[27] Seljom P, Tomasgard A. Short-term uncertainty in long-term energy system models A case study of wind power in Denmark. Energy Econ 2015;49:157–67. https://doi.org/10.1016/j.eneco.2015.02.004. https://linkinghub.elsevier.com/retrieve/pii/S0140988315000419.
[28] Nagl S, Fürsch M, Lindenberger D. The costs of electricity systems with a high share of fluctuating renewables: a stochastic investment and dispatch optimization model for Europe. Energy J 2013;34(4):151–79. https://doi.org/10.5547/01956574.34A8. http://www.iaee.org/en/publications/ejarticle.aspx?id=2529.
[29] Marañón-Ledesma H, Tomasgard A. Analyzing demand response in a dynamic capacity expansion model for the European power market. Energies 2019;12(15):2976. https://doi.org/10.3390/en12152976. https://www.mdpi.com/1996-1073/12/15/2976.
[30] Loulou R. Documentation for the TIMES model. Tech. Rep. July, energy technology systems analysis programme. 2016. http://iea-etsap.org/index.php/documentation.
[31] European network of transmission system Operators for electricity (ENTSO-e). Statistical Factsheet (May) (2016), https://docstore.entsoe.eu/Documents/Publications/Statistics/Factsheet/entsoe_sfs2015_web.pdf.
[32] Capros P, De Vita A, Tasios N, Siskos P, Kannavou M, Preopoulos A, Evangelopoulou S, Zampara M, Papadopoulos D, Nakos C, Paroussos L, Fragiadakis K, Tsani S, Karkatsoulis P, Fragkos P, Kouvaritakis N, Höglund-Isaksson L, Winiwarter W, Purohit P, Gomez-Sanabria A, Frank S, Forsell N, Gusti M, HAvlik P, Oberseiner M, Witzke H, Kestling M. EU reference scenario 2016 - energy, transport and GHG emissions - trends to 2050. 2016. https://doi.org/10.2833/9127. https://ec.europa.eu/energy/sites/ener/files/documents/20160713draft_publication_REF2016_v13.pdf.
[33] Brown T, Bischof-Niemz T, Blok K, Breyer C, Lund H, Mathiesen B. Response to Burden of proof: a comprehensive review of the feasibility of 100% renewable-electricity systems'. Renew Sustain Energy Rev 2018;92(September 2017):834–47. https://doi.org/10.1016/j.rser.2018.04.113. https://linkinghub.elsevier.com/retrieve/pii/S1364032118303307.
[34] GWEC, SolarPower Europe, Greenpeace. Energy [R]evolution: 100% renewable energy for all. 2015. https://doi.org/10.1515/9781400874750-006. https://storage.googleapis.com/planet4-canada-stateless/2018/06/Energy-Revolution-2015-Full.pdf.
[35] Breyer C, Bogdanov D, Aghahosseini A, Gulagi A, Child M, Oyewo AS, Farfan J, Sadovskaia K, Vainikka P. Solar photovoltaics demand for the global energy transition in the power sector. Prog Photovoltaics Res Appl 2018;26(8):505–23. https://doi.org/10.1002/pip.2950. http://wiley.com/10.1002/pip.2950.
[36] International Energy Agency (IEA). World energy Outlook 2018. 2018. https://www.iea.org/weo2018/.
[37] Marcu A, Alberola E, Caneill J-y, Mazzoni M, Schleicher S, Stoefs W, Vailles C. 2017 state of the EU ETS report. https://www.i4ce.org/wp-core/wp-content/uploads/2017/05/17-05-State_of_eu_ets_report_2017_updated.pdf; 2017.
[38] Bogdanov D, Farfan J, Sadovskaia K, Aghahosseini A, Child M, Gulagi A, Oyewo AS, de Souza Noel Simas Barbosa L, Breyer C. Radical transformation pathway towards sustainable electricity via evolutionary steps. Nat Commun 2019;10(1):1077. https://doi.org/10.1038/s41467-019-08855-1. http://www.nature.com/articles/s41467-019-08855-1.
[39] Zappa W, Junginger M, van den Broek M. Is a 100% renewable European power system feasible by 2050? Appl Energy 2019;233–234(November 2018):1027–50. https://doi.org/10.1016/j.apenergy.2018.08.109. https://linkinghub.elsevier.com/retrieve/pii/S0306261918312790.
[40] Pfenninger S. Dealing with multiple decades of hourly wind and PV time series in energy models: a comparison of methods to reduce time resolution and the planning implications of inter-annual variability. Appl Energy 2017;197:1–13. https://doi.org/10.1016/j.apenergy.2017.03.051. https://linkinghub.elsevier.com/retrieve/pii/S0306261917302775.
[41] Pfenninger S, Staffell I. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy 2016;114:1251–65. https://doi.org/10.1016/j.energy.2016.08.060. https://linkinghub.elsevier.com/retrieve/pii/S0360544216311744.
[42] Staffell I, Pfenninger S. Using bias-corrected reanalysis to simulate current and future wind power output. Energy 2016;114:1224–39. https://doi.org/10.1016/j.energy.2016.08.068. https://linkinghub.elsevier.com/retrieve/pii/S0360544216311811.
[43] Rienecker MM, Suarez MJ, Gelaro R, Todling R, Bacmeister J, Liu E, Bosilovich MG, Schubert SD, Takacs L, Kim G-K, Bloom S, Chen J, Collins D, Conaty A, da Silva A, Gu W, Joiner J, Koster RD, Lucchesi R, Molod A, Owens T, Pawson S, Pegion P, Redder CR, Reichle R, Robertson FR, Ruddick AG, Sienkiewicz M, Woollen J. MERRA: NASA's modern-era retrospective analysis for research and applications. J Clim 2011;24(14):3624–48. https://doi.org/10.1175/JCLI-D-11-00015.1. http://journals.ametsoc.org/doi/10.1175/JCLI-D-11-00015.1.
[44] European network of transmission system Operators for electricity (ENTSO-e), ENTSO-E transparency platform (2019). https://transparency.entsoe.eu/.
[45] Lindberg K, Seljom P, Madsen H, Fischer D, Korpås M. Long-term electricity load forecasting: current and future trends. Util Pol 2019;58(April):102–19. https://doi.org/10.1016/j.jup.2019.04.001. https://linkinghub.elsevier.com/retrieve/pii/S0957178719300116.
[46] Lund H. Large-scale integration of wind power into different energy systems. Energy 2005;30(13):2402–12. https://doi.org/10.1016/j.energy.2004.11.001. https://linkinghub.elsevier.com/retrieve/pii/S0360544204004736.
[47] Hoefnagels R, Junginger M, Panzer C, Resch G, Held A. Long term potentials and costs of RES Part I : potentials , diffusion and technological learning. Tech. Rep. RE-shaping (work package 5), intelligent energy– Europe. ALTENER; 2011. https://www.reshaping-res-policy.eu/downloads/D10_Long-term-potentials-and-cost-of-RES.pdf.
[48] Waagard IH, Christophersen EB, Slungård I. Mulighetsstudie for landbasert vindkraft 2015 og 2025 (Study of the potential of onshore wind 2015 and 2025. 2015. http://publikasjoner.nve.no/rapport/2008/rapport2008_18.pdf.
[49] Lako P. Technical and economic features of renewable electricity technologies. Tech. Rep. ECN-E–10-034, ECN (2010), https://www.ecn.nl/docs/library/report/2010/e10034.pdf.
[50] Kall P, Wallace SW. Stochastic programming. Chichester: John Wiley & Sons; 1994. https://www.stoprog.org/sites/default/files/files/manujw.pdf.
[51] Kaut M, Midthun KT, Werner AS, Tomasgard A, Hellemo L, Fodstad M. Multi-horizon stochastic programming. Comput Manag Sci 2014;11(1–2):179–93. https://doi.org/10.1007/s10287-013-0182-6. http://link.springer.com/10.1007/s10287-013-0182-6.
[52] van der Weijde AH, Hobbs BF. The economics of planning electricity transmission to accommodate renewables: using two-stage optimisation to evaluate flexibility and the cost of disregarding uncertainty. Energy Econ 2012;34(6):2089–101. https://doi.org/10.1016/j.eneco.2012.02.015. https://linkinghub.elsevier.com/retrieve/pii/S0140988312000436.
[53] Lund H. Excess electricity diagrams and the integration of renewable energy. Int J Sustain Energy 2003;23(4):149–56. https://doi.org/10.1080/01425910412331290797. http://www.tandfonline.com/doi/abs/10.1080/01425910412331290797.
[54] Child M, Kemfert C, Bogdanov D, Breyer C. Flexible electricity generation, grid exchange and storage for the transition to a 100% renewable energy system in Europe. Renew Energy 2019;139:80–101. https://doi.org/10.1016/j.renene.2019.02.077. https://linkinghub.elsevier.com/retrieve/pii/S0960148119302319.
[55] Lund H, Arler F, Østergaard P, Hvelplund F, Connolly D, Mathiesen B, Karnøe P. Simulation versus optimisation: theoretical positions in energy system modelling. Energies 2017;10(7):840. https://doi.org/10.3390/en10070840. http://www.mdpi.com/1996-1073/10/7/840.
[56] Wohland J, Reyers M, Märker C, Witthaut D. Natural wind variability triggered drop in German redispatch volume and costs from 2015 to 2016. PloS One 2018;13(1):e0190707. https://doi.org/10.1371/journal.pone.0190707. https://dx.plos.org/10.1371/journal.pone.0190707.
[57] Mesfun S, Leduc S, Patrizio P, Wetterlund E, Mendoza-Ponce A, Lammens T, Staritsky I, Elbersen B, Lundgren J, Kraxner F. Spatio-temporal assessment of integrating intermittent electricity in the EU and Western Balkans power sector under ambitious CO2 emission policies. Energy 2018;164(2018):676–93. https://doi.org/10.1016/j.energy.2018.09.034.
[58] Hansen K, Mathiesen BV, Skov IR. Full energy system transition towards 100% renewable energy in Germany in 2050. Renew Sustain Energy Rev 2019;102(July 2018):1–13. https://doi.org/10.1016/j.rser.2018.11.038. https://linkinghub.elsevier.com/retrieve/pii/S1364032118307913.
[59] Connolly D, Lund H, Mathiesen B. Smart Energy Europe: the technical and economic impact of one potential 100% renewable energy scenario for the European Union. Renew Sustain Energy Rev 2016;60:1634–53. https://doi.org/10.1016/j.rser.2016.02.025. https://linkinghub.elsevier.com/retrieve/pii/S1364032116002331.