Energy Economics 112 (2022) 106182

Contents lists available at ScienceDirect

Energy Economics

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

Long term power prices and renewable energy market values in Norway – A probabilistic approach

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ARTICLE INFO

Keywords:
Energy sector modelling
Global sensitivity analysis
Monte Carlo
Morris screening
Power and heat market
Uncertainty and risk

ABSTRACT

The transition to renewable energy will require large investments in renewable power generation capacity, made under large risks regarding future revenues. This study presents an analysis of different risk factors for future power prices and renewable energy market values in Norway, a region dominated by renewable power. We use a combination of global sensitivity analysis and Monte Carlo simulations to estimate the influence of the different parameters, including electricity demand, politically driven capacity constraints, fuel and carbon prices, investment costs of new generation capacity, and other production costs. The novelty of this study lies in the thorough analysis of how the future power market may be affected by the above-mentioned risk factors using a probabilistic approach. The results show that the carbon price and natural gas prices remain the two major power price drivers in 2040, despite lower fossil fuel shares. The mean annual Norwegian power price from the Monte Carlo simulations is estimated to be 39 ± 4 €/MWh and long-term price levels below 23 €/MWh or above 50 €/MWh seem highly unlikely in an average weather year. The market values of renewable power technologies differ substantially with hydropower at 53 ± 6 €/MWh, onshore wind at 32 ± 4 €/MWh, offshore wind at 33 ± 3 €/MWh, and solar PV as low as 20 ± 3 €/MWh. By comparing these market values to LCOE estimates in the literature we estimate 98% and 2% probabilities that revenues from onshore wind and solar PV will be within a half standard deviation away from their LCOE. We conclude that for the 2040 power prices, international drivers will be more important than price drivers inside the Norwegian market, and that policy support would continue to be necessary for large-scale deployment of offshore wind and solar PV in Norway.

1. Introduction

The power sector faces substantial risks from many different sources, for instance, fuel markets, climate and energy policies, technological development, weather variability and climate change. Understanding the impacts and uncertainty of all these drivers is crucial for long-term energy system planning and investment decisions. In particular, the uncertainty in these drivers may have large consequences for the transition to renewable energy sources, and the design of policies necessary to achieve such a transition.

The decreasing costs of wind and solar power have increased their competitiveness compared to fossil fuel alternatives (IRENA, 2021), resulting in rapidly increasing levels of renewable power generation in Europe. However, as observed by several recent studies (Figueiredo and da Silva Pereira, 2017; Hirth, 2018; López Prol et al., 2020; Ozdemir et al., 2017; Tveten et al., 2013), higher renewable generation capacities have caused electricity prices to decrease due to the merit order effect. In addition, the prices received by renewable technologies, often referred to as their *market values*, decline more than the average power price, due to the so-called merit-order effect.[1] The reason for this reduction is that the renewable technologies themselves depress prices in periods of high wind speeds or clear weather (Hirth, 2013; Tveten et al., 2016; Winkler et al., 2016). This results in a lower *value factor*[2] for the renewables as their share in the power mix increases, and there are serious concerns that this so-called cannibalisation effect could prevent renewables from recovering their costs in the market and thereby cause low investment in

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[1] Merit-order effect is the effect that a wind or solar power plant produces electricity at the same time as the neighbouring power plant, in that way reducing the power prices in the hours it is producing.

[2] Value factor is defined as the market value of a specific technology divided by the market prices, for each hour.

https://doi.org/10.1016/j.eneco.2022.106182
Received 18 August 2021; Received in revised form 4 May 2022; Accepted 6 July 2022
Available online 13 July 2022

renewables or a high dependency on support policies. Brown and Reichenberg (2021), however, expect that regions with large amounts of flexibility may be less susceptible to the merit-order effect, and it is therefore of great interest to study this for a region dominated by flexible hydropower, such as Norway. Several studies have looked into the *rebound effect*[3] of renewable energy (Galvin et al., 2021; Jia and Lin, 2022; Keyes et al., 2019; Meng and Li, 2022; Vélez-Henao et al., 2020). They find that increased renewable generation results in increased energy demand rather than a decrease in fossil consumption, this will likely increase the need for generation capacity more than a one-to-one substitution with the fossil counterpart.

Studies on the revenues of renewable generation often calculate market values for exogenously predetermined shares of renewables, and therefore pay less attention to the underlying drivers of power prices and market values. As shown by Chen et al. (2021a) and others, long-term power market studies show that there is large uncertainty about future electricity prices. The main sources of risk identified in the literature review by Chen et al. (2021a) are future fuel prices, technological development, social acceptance of variable renewables, international and national policies, and the pace of electrification. Given the large uncertainties faced by the energy sector, it is important to understand how market values react to the different factors, and what implications this may have for the transition to renewable energy.

Among previous studies on uncertainties and risk factors in the power market, Nie et al. (2018) used fuzzy-probability programming in a power model and found that electricity demand and expenditure on electricity imports have significant effects on system costs. Bistline and Weyant (2013) used stochastic programming to study technological and policy-related uncertainties in the US power sector, concluding that including uncertainty in capacity planning may reduce the risks due to uncertain climate policy. Pye et al. (2015) analysed uncertainty in energy transition pathways for the UK and found that investment costs, fuel prices, and fuel availability are the most uncertain parameters. These studies demonstrate the importance of using global sensitivity analysis to provide a more complete understanding of the energy system.

Other studies, for instance, a study by Fais et al. (2016), point out the importance of uncertain technological development. They estimated the impact of technological uncertainty on the UK energy system using global sensitivity analysis and found that the availability of a technology may have a large impact on rest of the energy system. Similarly, Pizarro-Alonso et al. (2019) study different risk factors affecting Danish electricity prices and wind generation capacity using global sensitivity analysis. One of the conclusions was that the learning effect of offshore wind technology is one of the most important factors for lowering electricity prices. Pizarro-Alonso et al. (2019) also point out that it is important that an overall energy system analysis covers the entire uncertainty space, since local methods may not find all influential parameters. However, only technological uncertainty was considered in the study, not policy-driven uncertainties.

Most long-term power market studies do not carefully incorporate risks in their investigations. As shown by previous studies, however, it is crucial for policymakers and investors to understand the main risk factors and how they interact in order to improve planning and decision-making in the power sector.

In this context, this study addresses two main questions, which have previously received limited attention in the literature: (i) what are the main driving forces of future power prices and (ii) how do these drivers affect price levels, risk, and renewable market values? These questions may be investigated using different sensitivity methods, which can be divided into local and global methods. Most common are local methods, which determine the sensitivity to a single point or variable of the input space. Global methods, however, determine the sensitivity with respect to multiple (or all) variables of the input space. The difference may be significant since a local method will not be able to find correlated and non-linear effects that a global method will be able to estimate (Saltelli et al., 2019). Morris screening is a global method with relatively low computational cost (Morris, 1991), which identifies and ranks the most significant variables using a low number of simulations compared to other sensitivity methods (Borgonovo and Plischke, 2016; Herman et al., 2013). Herman et al. (2013) underline the need for carrying out a global sensitivity analysis in order to find the true output risk of a system.

Our study is the first to perform a global sensitivity analysis focusing on future power prices and renewable market values using a market modelling approach with a high temporal and spatial resolution. In addition, we consider a wider range of risk factors in our analysis compared to most previous studies. We use the Balmorel energy system model to determine the impact of different sources of risk on the future power price, which allows consistent and detailed modelling of the power and heat sectors in Northern Europe at a high spatial and temporal resolution. We use the Morris screening method developed by Pizarro-Alonso et al. (2019) together with the Balmorel model to identify the main risk factors affecting power prices, but with two important differences. Firstly, we focus mainly on the Norwegian power sector instead of the Danish energy system. Whereas the Danish system relies more heavily on wind power, the Norwegian power system relies primarily on hydropower, as such our study may lead to additional insights which should transfer more easily to regions dominated by hydropower. Secondly, we go beyond investigating technological risks, as our study includes a larger range of uncertainty sources. We include uncertainties on both the supply and demand sides, including fuel price risk and policy risks such as socially acceptable investment levels for different technologies. After identifying the main risk factors with the Morris screening method, we perform a formal uncertainty analysis using Monte Carlo analysis with Latin hypercube sampling to quantify levels and uncertainty ranges for future power prices and renewable market values. Morris screening will enable us to rank drivers according to their impact on power prices, and the formal uncertainty analysis will allow us to understand the impact of the main drivers more profoundly. In our subsequent analysis, we pay special attention to the market values of different renewable energy sources, which are fundamental to the energy transition and may have important implications for energy policy.

The next chapter first provides a brief overview of the Norwegian energy system, before presenting details on how the different methods – the Balmorel energy system model, the Morris screening method, and the Monte Carlo simulations – are combined to achieve the objectives of the study, as well as the operational assumptions for the input parameters. The third chapter presents and synthesizes the main results: which drivers were identified by the Morris screening method as most influential for the future power price, detailed quantification of the impacts of the main drivers, and their effects on price, revenue and market value risk. The fourth chapter further discusses the implications of the results for the energy transition and energy policy. In the fifth and final chapter, we summarise the main findings of the study and raise some additional research questions.

2. Method

This chapter includes a brief introduction to the Norwegian power market (Section 2.1). The Balmorel energy system model is described in Section 2.2, followed by two sections presenting the global sensitivity approach used in this study, with Morris screening in Section 2.3 and Monte Carlo simulations in Section 2.4. Finally, in Section 2.5, we discuss the ranges and probability distributions of the input parameters to the Morris screening method and the Monte Carlo analysis.

[3] Rebound effect is that increased use of a technology efficiency is followed by increased raw material use and not a decrease.

2.1. The Norwegian power system

In 2021, Norway had an electricity production of 157 TWh, of which 91% was from hydropower, 8% from onshore wind, and <1% from thermal sources (NVE, 2021b). This shows that the Norwegian generation mix is already dominated by renewable energy. In normal weather years, Norway exports around 19 TWh of electricity to neighbouring countries. Due to electrification of transport and industrial processes, demand is expected to increase from 138 TWh in 2021 to 174 TWh in 2040 (NVE, 2021b). This will cause pressure for increasing the generation capacity, but today there are few socially accepted options for capacity expansions. In particular, onshore wind has met fierce public opposition the latest years, and it seems unlikely that the onshore wind generation capacity will be increased in the coming years. Norwegian power prices have historically been in the range of 20–40 €/MWh (NVE, 2021b), among the lowest in Europe, and studies predict that the prices will stay within the range of 40–60 €/MWh towards 2040 (NVE, 2021b).

2.2. Balmorel energy system model

Balmorel is a partial equilibrium model of the North European heat and power market. The model has been continuously updated (Wiese et al., 2018) since the first version was developed by Ravn et al. (2001). Both the model code and the input data are available from the Balmorel community Github Repository (2021). The entire model and the input data are open access and published under an ISC license (Open Source Initiative, 2020). The model is easily extendable and adaptable, and recent studies have used the model for estimating the effects of cross border power transmission (Chen et al., 2020), social acceptance of generation technologies (Bolwig et al., 2020), EV charging flexibility (Gunkel et al., 2020), displacement of fossil fuels by biomass in the power and heat sector (Jåstad et al., 2020), sector coupling (Gea-Bermúdez et al., 2021), and the impact of decentralized heating (Chen et al., 2021b) within the North European power and heat market.

Balmorel minimizes the total costs of generating and transmitting heat and electricity in order to satisfy an exogenously defined demand profile. To meet the demand in each region at every timestep, the model selects the optimal dispatch of generation technologies, energy storages, and electricity transmission that minimizes the yearly costs, given a set of constraints. A simplified flowchart of the model is shown in Fig. 1. In addition to assumptions about available generation capacity in 2040 based on existing capacity (adjusted for their techno-economic lifetime) and known investments – summarized in Table 1 – the model permits investments in additional generation capacity. The objective function incorporates costs related to investments in grid and generation capacity, operation and management costs (both fixed and variable), fuel costs, costs related to transmission losses, storages, consumption, and taxes. The optimization is done for 2040 without any endogenous information for years prior to or after 2040.

The model assumes perfect foresight within the year and a perfectly competitive market. Although these are strong assumptions, they are common assumptions in detailed energy system models and are necessary to keep the model computationally tractable. The effects of these assumptions on the results are also relatively well understood. The assumption of perfect competition allows the optimisation problem to be expressed as a single objective function, but results in prices somewhat below what one would expect of imperfect competition. We expect the departure to be modest in the case of the Nordic power market, given that Lundin and Tangerås (2020) have established that the Nordic power market is consistent with Cournot competition with a price-cost margin of around 4 %. The assumption of perfect foresight in energy system

Table 1
Exogenously defined generation capacity in 2040, based on existing and known investment of generation equipment and remining techno economical lifetime in 2040, unit: GW.

	Rest of model	Norway	Sweden	Denmark	Finland
Natural gas	63	0	0	0	1
Fuel Oil	5	0	2	0	1
Coal	24	0	0	0	0
Other fossil	13	0	1	0	1
Biomass	22	0	3	0	1
Waste	4	0	17	0	14
Hydro	181	See scenario		0	3
Solar	64	assumption in		1	0
Nuclear	59	Table 5.		See scenario	
Onshore wind	40			assumption in Table 5.	
Offshore wind	15				

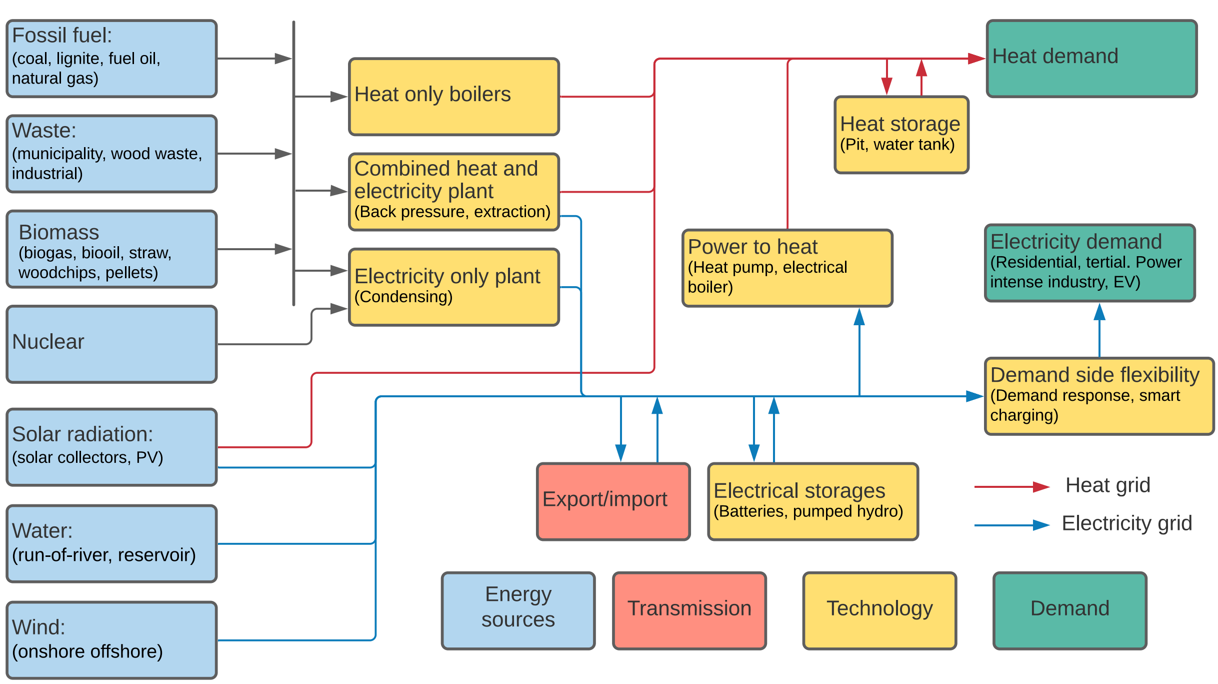

Fig. 1. Flowchart of the model with the main fuels and technologies used in the model, the system is optimized simultaneously for all regions and timesteps.

models is known to produce more stable prices than models without perfect foresight, and tends to result in capacity underinvestment in planning models (Ringkjøb et al., 2020; Seljom et al., 2017; Seljom et al., 2021). Since generation capacities in the Nordic region will be given exogenously in our setup, we do not expect the perfect foresight assumption to have a large impact on our results.

The model covers the interconnected heat and electricity market in Northern Europe (i.e., Belgium, Germany, Denmark, Estonia, Finland, France, Latvia, Lithuania, The Netherlands, Norway, Poland, Sweden, and the UK). There are a total of 24 electricity regions, which mainly correspond to the NordPool regions (NordPool, 2021) and 64 heat regions (Fig. 2). The model allows electricity transmission with existing transmission lines and known future expansions (Table 2 and Fig. 1). In addition, we allow endogenous investment in new transmission lines between the regions, restricted upwards to 2 GW between regions in the Nordic countries, 2 GW between the Nordic regions and the rest of European countries modelled, and 5 GW within the remaining European regions. We have included these constraints on investments in transmission lines in order to reflect the current strong political and public opposition to transmission lines. We assume that all heat produced within a region must be consumed within the same region.

To limit the computational time, we use representative time periods consisting of 288 timesteps. The original timeseries data, such as wind generation, solar generation, and consumption are given at an hourly resolution, and in order to select representative periods, the data are aggregated with an algorithm that maintains the maximum, minimum, and mean values within each week based on Koduvere et al. (2018). Fig. 3 shows duration curves for the selected profiles in NO2.

Table 3 shows the assumed electricity consumption which is divided into four groups having different demand profiles and levels of flexibility. Electricity consumption for EV charging and flexibility provided by smart EV charging is based on (Gunkel et al., 2020). Demand response potential in the power-intensive industries, Residential, and Other category is based on Kirkerud et al. (2021). In addition, the

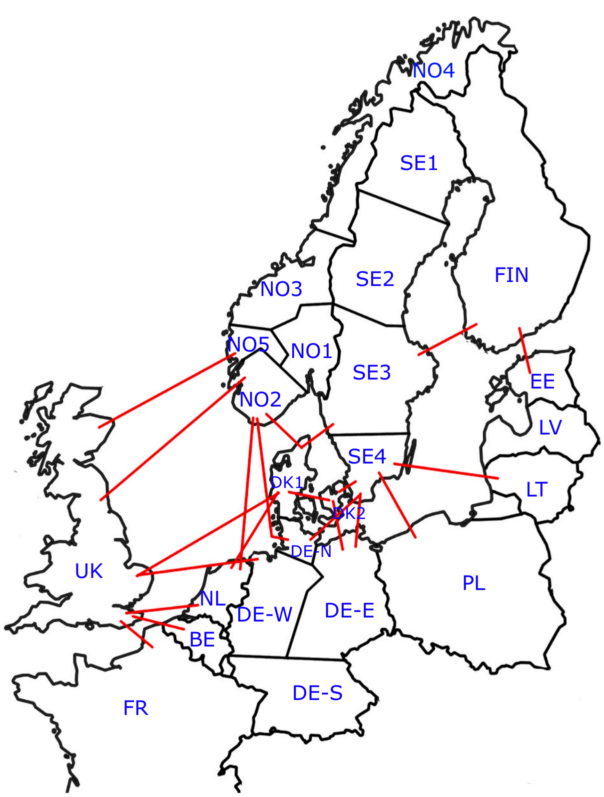

Fig. 2. Electricity regions and offshore interconnectors in Balmorel.

Table 2
Exogenously defined transmission line capacity inside, between, and from the Nordic countries. Unit: GW, source: (Entso-E, 2018; NordPool, 2021).

	DK	NO	SE	FI	DE	NL	UK	ROW
DK	0.6	1.6	2.4		4.0	0.7	1.4	
NO	1.6	8.9	3.7		1.4	0.7	2.8	
SE	2.0	4.0	16.5	3.2	1.3			1.3
FI			3.2		0.0			1.0
DE	4.0	1.4	1.3		35.1	5.0	1.4	7.5
NL	0.7	0.7			5.0		1.0	3.4
UK	1.4	2.8			1.4	1.0		7.8
ROW			1.3	1.0	8.5	3.4	7.8	7.3

electricity consumption for power to heat technologies in district heating is modelled endogenously in the model and is flexible.

Balmorel models electricity generation from the most common energy sources, including wind (onshore and offshore), solar (solar collectors and PV), hydropower (run-of-river, reservoir, and pump), biomass (biogas, biooil, straw, woodchips, and pellets), fossil fuels (coal, lignite, fuel oil, and natural gas), and other fuels such as waste and nuclear power. Fuel prices are based on IEA (2018), and nuclear generation costs are from Entso-E (2020). Table 4 shows the main assumption regarding techno-economic data for 2040, with investment cost, variable and fixed operation and management costs, and fuel efficiency for the different technology groups. The costs are given as ranges, reflecting variation between different vintages of the technologies.

The potential expansion of renewable generation is geographically restricted, based on techno-economic assumptions and availability. For the purposes of this study, expansions of variable renewable generation capacity in the Nordic countries are defined exogenously. In this sense, we assume that the investment in new facilities will happen at the most economically attractive locations that are available within each country.

2.3. Ranking input parameter importance with Morris screening

Morris screening was first described by Morris (1991). The method is based on an efficient sampling method for input parameters and calculating the elementary effects of each single input. The Morris method is a version of the common used one-at-a-time method in sensitivity analysis (Garcia Sanchez et al., 2014), but instead of returning to the base values after studying one parameter, the method changes one variable at a time in a random order without returning to the base values. The method thereby traverses the input space following a random path, and is therefore able to determine which input factors that have no influence, linear, and nonlinear effects on the outcome of a model (Iooss and Lemaître, 2015).

The Morris method is based on a Monte Carlo evolution of points along a multi-step trajectory through the input space. The trajectory is chosen as follows: (1) choose a random starting point in the input space; (2) choose one random parameter that changes with a fixed step length of Δ in a random direction, while the other parameters remain unchanged; (3) repeat the second step until all k parameters have been changed once; and (4) repeat steps 1–3 r times. The step length Δ is equal to $\frac{p}{2(p-1)}$, where p is the number of unique levels that has equal probability of being chosen. The samples are assumed to be uniformly distributed in the hypercube, and then transformed to the real uncertainty distribution. In this study, p is chosen to be 8, which gives a step length of $\Delta = \frac{4}{7}$ of the solution space. Use of k parameters will need $r(k+1)$ simulations for identifying unimportant parameters in the input space, where r is the number of repetitions. The method of sampling the input parameters allows $r \ll k$, and r is usually between 4 and 15 repetitions (Campolongo et al., 2007).

The Morris screening results in an input matrix $\mathbf{X} = [X_1, \ldots, X_i, \ldots, X_k]$ where X_i represents the different inputs of parameter i. The matrix $\mathbf{X}$

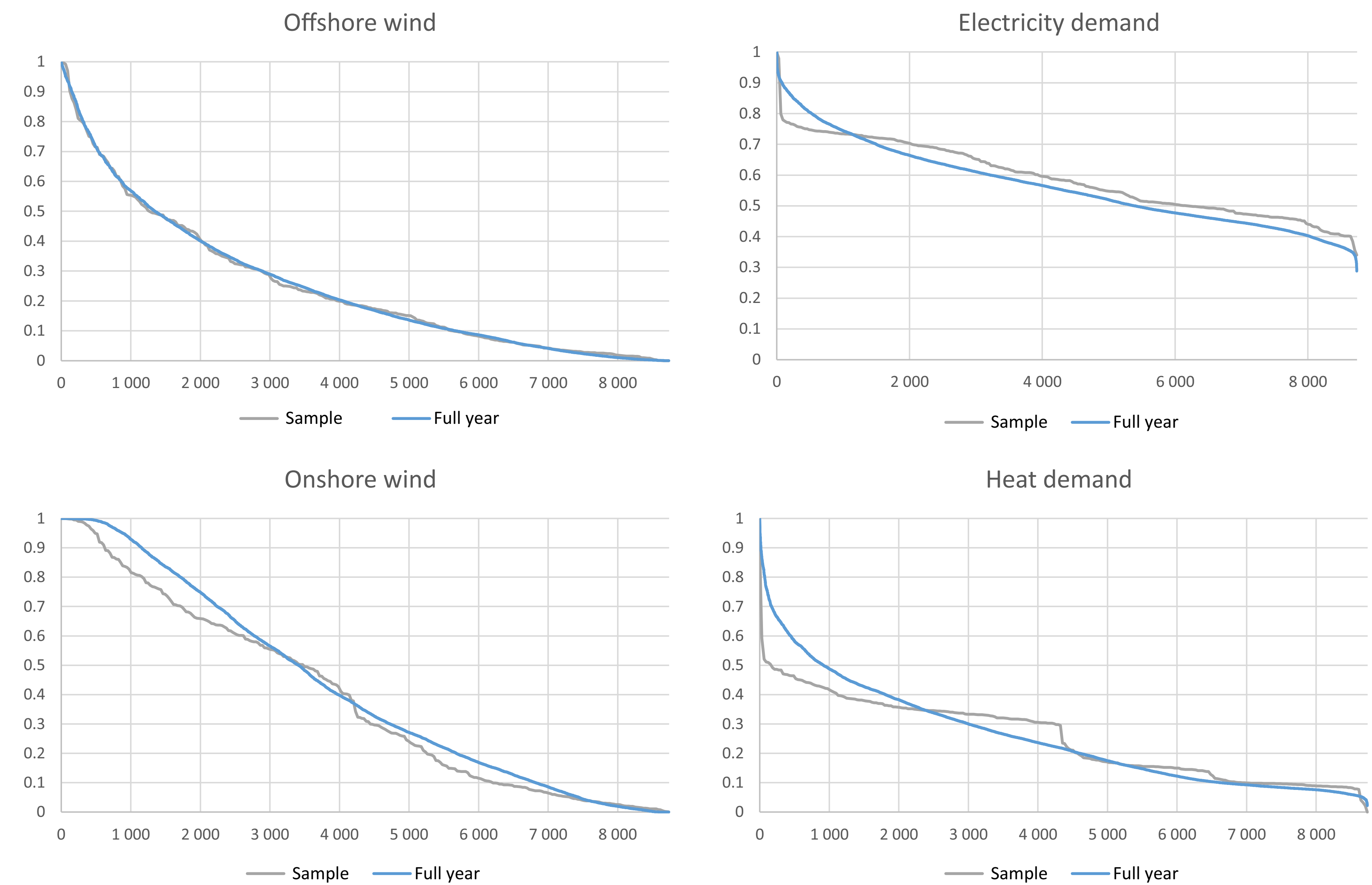

Fig. 3. Duration curves for wind profiles and demand in NO2 of the model data sample and actual full-year observations. The y-axis shows fraction of the highest value per year. For the sample is the x-axis extended in order to represent a full year.

Table 3
Demand for different electricity and heat categories in the modelled countries in 2040. Unit: TWh.

	Power-intensive industry	Residential	Other	EV	District heat
Belgium	25	19	39	4	7
Germany	130	128	272	33	248
Netherlands	22	23	66	15	19
France	56	159	232	28	25
United Kingdom	39	108	164	28	18
Poland	26	29	89	13	88
Estonia	1	2	5	1	5
Lithuania	1	3	7	2	6
Latvia	0	2	4	1	6
Norway	See scenario assumption in Table 5.				7
Sweden					47
Denmark					32
Finland					32

consists of k columns and r rows, one row for each single simulation. For simplicity, we assume that there is only one single interesting output from the Balmorel model, represented by $y(\mathbf{X})$. After running all r simulations in Balmorel, the elementary effects EE of each input parameter i and repetition j can be calculated by:

$$EE_i^{(j)} = \frac{\partial y^{(j)}}{\partial X^{(j)}} = \frac{\left(y^{(j)}(X_1, X_2, \ldots, X_{i-1}, X_i + \Delta, X_{i+1}, \ldots, X_k) - y^{(j)}(X_1, X_2, \ldots, X_{i-1}, X_i, X_{i+1}, \ldots, X_k)\right)}{\Delta} \quad (1)$$

In order to give all $EE_i^{(j)}$ the same scale, the elementary effects are scaled according to the standard deviations of the input and output (sigma-scaled elementary effects):

$$SEE_i^{(j)} = EE_i^{(j)} * \frac{s_i}{s_y} \quad (2)$$

where s_i is the standard deviation of the input parameter i and s_y is the standard deviation of the output. We then calculate the mean (μ_i) and the standard deviation (σ_i) of the sigma-scaled elementary effects:

$$\mu_i = \frac{1}{r}\sum_{j=1}^{r}\left(SEE_i^{(j)}\right) \quad (3)$$

$$\sigma_i = \sqrt{\frac{1}{r}\sum_{j=1}^{r}\left(SEE_i^{(j)} - \frac{1}{r}\sum_{j=1}^{r} SEE_i^{(j)}\right)^2} \quad (4)$$

where r is number of repetitions, i is the number of the input parameter, k is the number of input parameters in the simulations, and j is the repetition number. $SEE_i^{(j)}$ is the sigma-scaled elementary effects of input parameter i in simulation j. The elementary effects are used for calculating descriptive statistics μ_i, which is the mean of the elementary effects for variable i, and σ_i, which is the standard deviation of the elementary effects for variable i. The mean and standard deviation of the scaled elementary effects can be interpreted as how much the variable influences the results and how much variability the variable causes in the results. If the variable has a high standard deviation compared to the mean, the variable might have non-linear effects on the outputs or it may interact strongly with other variables (Branger et al., 2015; Iooss and Lemaître, 2015). The importance of the parameters can be ranked by μ_i, which quantifies the overall influence of the parameter (Yang, 2011). However, the ranking is only qualitative and the mean μ_i does not allow us to determine exactly how much more important one parameter is

Table 4
Main techno-economic assumptions used. Numbers shown are maximum and minimum ranges assumed in 2040. Source: (Energistyrelsen, 2020; IEA, 2016).

	Investment cost [M€/MW], for storage [M€/GWh]	Variable O&M except fuel costs [€/MWh]	Fixed O&M [€/MW]	Fuel efficiency/ COP [%]	Exogenously installed capacity [GW], for storage [GWh]	Base fuel cost [€/GJ]
Hydropower		0–10	22	100	87	
Hydropower pumped	0.29–2	0–1.06	0.14–0.14	73–76	146	
Onshore wind	0.96–3.5	1.2–2.7	11–25		49	
Offshore wind	1.5–2.2	2.3–3.8	30–51		16	
Solar collectors	0.23–0.47	0.32–0.56	0.05–0.10		0.61	
PV	0.25–0.72		5.2–9.3		64	
Natural gas	0.45–2.2	0.51–12	0.26–12	15–90	25	7.81
Natural gas-Heat Only	0.05–0.29	0.41–1.1	1.2–9.5	85–106	39	7.81
Coal	0.12–1.9	0.33–2.2	3.6–60	13–100	24	2.74
Lignite		2.0	56	30–41	10	0.86
Fuel oil		0.13–19.6	2.0–37	27–100	8	11.8
Peat	3.0–5.4	0.14–1.6	3.0–264	38–116	0.39	1.82
Other fossil	0–1.38	0–37	0–33	25–90	4.3	2.0–16.3
Waste	1.7–9	0.35–196	6.7–323	23–110	4.5	−3.26
Pell	0.67–3.0	0.5–1.0	3.0–34	90–102	0.91	12.4
Chips-CHP	0.61–5.4	0.15–274	6.7–59	85–118	5.4	10.1
Chips-Heat Only	0.61	1.3	39	90–112	11	10.1
Straw	0.78–4.9	0.16–3.5	37–240	17–110	6.8	8.96
Biogas	0.63–0.86	0.44–9.8	2.0–26	37–96	0.91	12.7
Biooil		1.1	2.0	90–100	1.2	27.8
Heat Pump	0.49–1.4	1.6–2.0	2.0	3.4–5.0	0.3	
Waste heat			30	100	0.9	0.09
Nuclear	6.0	2.3–4.2	116–123	33–37	67	0.76
Batteries	52–253		0.22–1.6	95		
Pit	0.40–1.3		0.003	70	12	
Water tank	2.9–3.8		0.01	98	18	

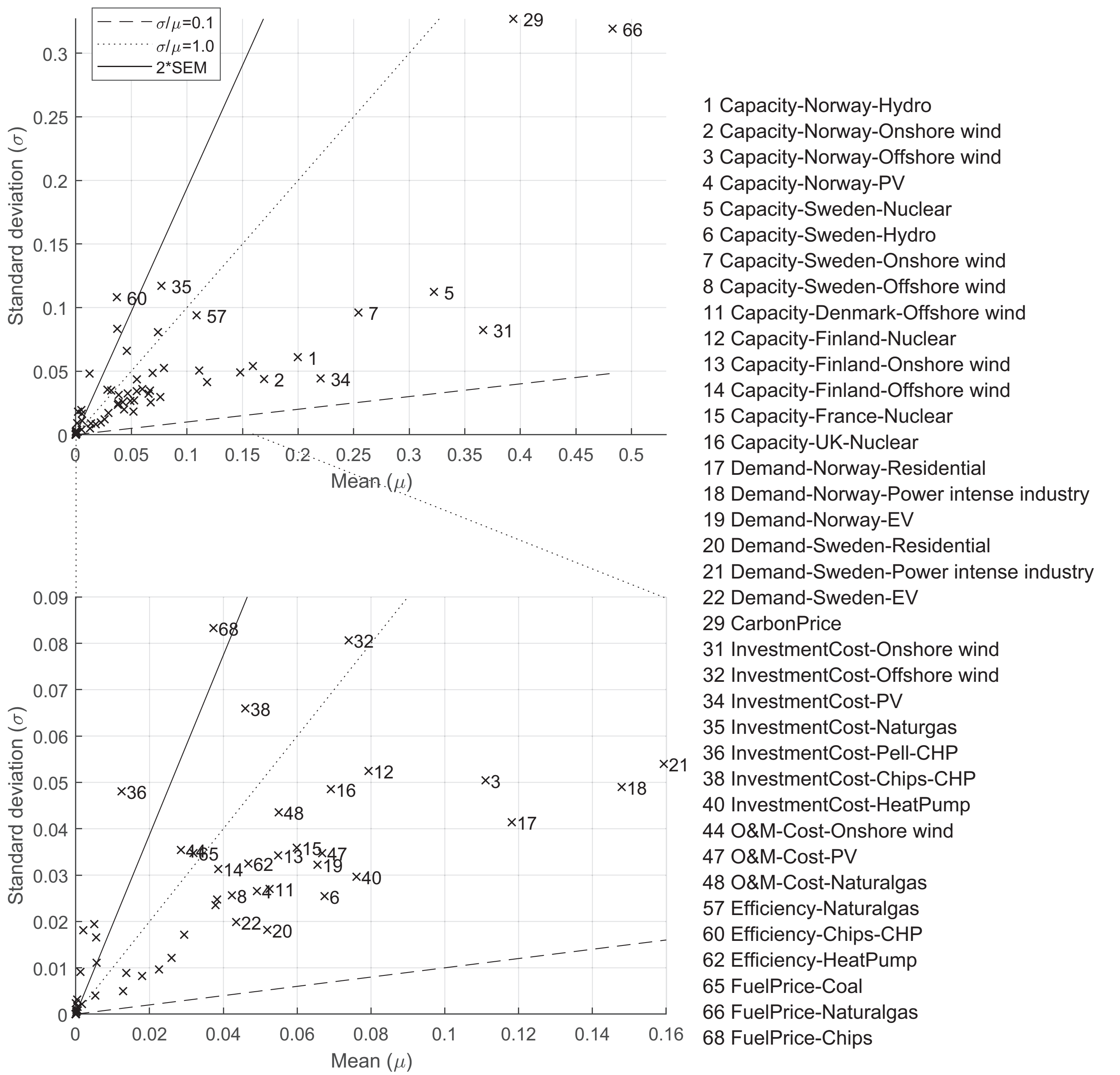

Fig. 4. The standard deviation and the absolute value of the mean of the elementary effects plotted together. The top figure shows the full chart, while the bottom figure shows the bottom left corner. Values to the right of the line 2*SEM (standard error of the mean) contribute significantly to the observed variation. In general, variables in the upper part of the figure have greater interaction effects than variables in the lower part. Variables to the right contribute more to the observed variation than variables to left. Factors below the line $\sigma/\mu = 0.1$ have a linear impact, factors in the range $0.1 < \sigma/\mu < 1$ are negligible for small μ values or influential for higher μ values, while factors to the left of the line $\sigma/\mu = 1$ have strong non-linear effects on the results. The upper figure includes all variables considered in the study, and the lower figure zooms in on the bottom left corner of the upper figure.

compared to another parameter (Mavromatidis et al., 2018).

Garcia Sanchez et al. (2014) divide the connection between the average and standard deviation of each parameter into three groups: first, a group with negligible effects, consisting of parameters with low average and low standard deviation. A second group, which is linear and additive, characterised by high average and low standard deviation. We categorise parameters in this group if $\frac{\sigma_i}{\mu_i} < 0.1$, as this suggests that the variation may be explained mainly by the change in the single input parameter. Therefore, when $\frac{\sigma_i}{\mu_i} < 0.1$, the factor has no or little interaction with the other factors. The third group consists of parameters with non-linearities or involved interactions with other input parameters, characterised by a high standard deviation compared to the mean. We classify parameters as belonging to this group if $\frac{\sigma_i}{\mu_i} > 1$, suggesting that the effect of one parameter depends on the level of at least one other parameter. In addition, we include a fourth group, which consists of the most important variables that have both a high standard deviation and a high average. That is, when $0.1 < \frac{\sigma_i}{\mu_i} < 1$, there is moderate interaction with other parameters.

As an objective criterion for when a parameter has a significant impact on the output, the figures also show a line for the standard error of the mean, calculated as $sem_i = \frac{\sigma_i}{\sqrt{r}}$.

Table 5
Probability distributions of input parameters assumed in the Morris sampling process.

Group	#	Parameter	Distribution type	Lower bound	Upper bound/ standard deviation	Mean	Unit	Source
Capacity	1	Norway-Hydro	Triangular	32.6	39.1	34.3	GW	(NVE, 2020), own
	2	Norway-Onshore wind	Triangular	5	13	9.2		(Chen et al., 2021a; NVE, 2020)
	3	Norway-Offshore wind	Triangular	1	5	1.83		
	4	Norway-PV	Triangular	0	10.5	2		(Chen et al., 2021a)
	5	Sweden-Nuclear	Triangular	0	10.8	5.29		
	6	Sweden-Hydro	Triangular	16.3	19.5	17.1		(NVE, 2020), own
	7	Sweden-Onshore wind	Triangular	6	24	12.9		(Chen et al., 2021a; NVE, 2020)
	8	Sweden-Offshore wind	Triangular	1	5	2.14		
	9	Sweden-PV	Triangular	3	10	4		(Chen et al., 2021a)
	10	Denmark-Onshore wind	Triangular	4	6.2	4.44		(Chen et al., 2021a; NVE, 2020)
	11	Denmark-Offshore wind	Triangular	5	12	5.56		
	12	Finland-Nuclear	Triangular	4	7.25	4.3		(Chen et al., 2021a)
	13	Finland-Onshore wind	Triangular	3	12	3		(Chen et al., 2021a; NVE, 2020)
	14	Finland-Offshore wind	Triangular	0	5	1		
	15	France-Nuclear	Triangular	32	55	42		(Chen et al., 2021a)
	16	Capacity-UK-Nuclear	Triangular	6	17	8		
Demand	17	Norway-Residential	Triangular	51	71	63	TWh	(Chen et al., 2021a; NVE, 2020)
	18	Norway-Power intense industry	Triangular	69	97	78		
	19	Norway-EV	Triangular	8	21	15		
	20	Sweden-Residential	Triangular	69	88	80		
	21	Sweden-Power intense industry	Triangular	46	82	67		
	22	Sweden-EV	Triangular	4	20	11		
	23	Denmark-Residential	Triangular	19	30	25		
	24	Denmark-Power intense industry	Triangular	12	24	18		
	25	Denmark-EV	Triangular	8	11	10		
	26	Finland-Residential	Triangular	41	59	50		
	27	Finland-Power intense industry	Triangular	52	69	61		
	28	Finland-EV	Triangular	4	6	5		
Other	29	Carbon Price	Triangular	10	130	57	€/tonne	(Chen et al., 2021a)
Investment costs	30	Waste	Triangular	−27%	37%	0%	Change from base value, shown in Table 4	(Energistyrelsen, 2020)
	31	Onshore wind	Triangular	−17%	75%	0%		
	32	Offshore wind	Triangular	−20%	10%	0%		
	33	Solar collectors	Triangular	−13%	14%	0%		
	34	PV	Triangular	−36%	22%	0%		
	35	Natural gas	Triangular	−33%	63%	0%		
	36	Pell-CHP	Triangular	−24%	46%	0%		
	37	Pell-Heat Only	Triangular	−17%	46%	0%		
	38	Chips-CHP	Triangular	−23%	43%	0%		
	39	Chips-Heat Only	Triangular	−29%	92%	0%		
	40	Heat Pump	Triangular	−22%	38%	0%		
	41	Natural gas-Heat Only	Triangular	−30%	400%	0%		
	42	Biogas	Triangular	−6%	41%	0%		
Operation and management costs	43	Waste	Triangular	−27%	29%	0%		
	44	Onshore wind	Triangular	−20%	10%	0%		
	45	Offshore wind	Triangular	−20%	20%	0%		
	46	Solar collectors	Triangular	−13%	0%	0%		
	47	PV	Triangular	−26%	29%	0%		
	48	Natural gas	Triangular	−25%	75%	0%		
	49	Pell-CHP	Triangular	−32%	31%	0%		
	50	Pell-Heat Only	Triangular	−22%	33%	0%		
	51	Chips-CHP	Triangular	−39%	31%	0%		
	52	Chips-Heat Only	Triangular	−79%	150%	0%		
	53	Heat Pump	Triangular	−25%	40%	0%		
	54	Natural gas-Heat Only	Triangular	−41%	120%	0%		
	55	Biogas	Triangular	−33%	100%	0%		
Conversion effectivity	56	Waste	Triangular	−20%	14%	0%		
	57	Natural gas	Triangular	−20%	5%	0%		
	58	Pell-CHP	Triangular	−8%	41%	0%		
	59	Pell-Heat Only	Triangular	−12%	1%	0%		

(continued on next page)

Table 5 (*continued*)

Group	#	Parameter	Distribution type	Lower bound	Upper bound/ standard deviation	Mean	Unit	Source
	60	Chips-CHP	Triangular	−10%	43%	0%		
	61	Chips-Heat Only	Triangular	−12%	14%	0%		
	62	Heat Pump	Triangular	−23%	1%	0%		
	63	Natural gas-Heat Only	Triangular	−10%	2%	0%		
	64	Biogas	Triangular	−11%	2%	0%		
Fuel price	65	Coal	Normal		32%	2.74	€/GJ	(Chen et al., 2021a)
	66	Natural gas	Normal		26%	7.81		
	67	Fuel Oil	Normal	0	106%	11.8		
	68	Chips	Normal		9%	10.1		(Energimyndigheten, 2020)
	69	Pell	Normal		11%	12.4		

2.4. Quantifying factor impacts with Monte Carlo simulations

The Morris screening process will distinguish between important and unimportant price drivers and establish the range of possible outcomes. Subsequently, we perform a formal uncertainty analysis using Monte Carlo simulations that quantify the impacts of the main factors. In order to keep the number of simulations at a tractable level, we sample only the twenty most important factors identified by the Morris screening, while all other values remain at their reference values.

In Monte Carlo simulations (Metropolis and Ulam, 1949), several deterministic simulations are performed with random input values sampled from probability distributions. Each of the set of random inputs is independent, which ensures fully independent simulations. Although Balmorel is a deterministic model, this method does not require any modifications to Balmorel since all changes are done solely in the input parameters. For mapping the entire solution space as fast as possible, we use Latin hypercube sampling (McKay, 1992). Latin hypercube sampling is regarded as an efficient sampling method for Monte Carlo simulation, without reducing mutual independence (Soroudi and Amraee, 2013). The sampling method is performed in three steps: first, divide each probability distribution in n segments, where each of the segments has a marginal probability of exactly $1/n$, then choose one random point within each segment. Second, repeat the first step for all k probability distributions. Third, randomly change the order of each of the n segments independently for all k distributions. This method will ensure that each of the segments will only be tested once and still ensure a random structure. In this study we chose $n = k$ and we add new hypercubes until the results converge.

2.5. Assumed probability distributions of the input parameters

Table 5 shows the probability distributions for different power price drivers that we assume in this study. The numbers are based on a comprehensive review of assumptions used in outlook reports by energy market experts and authorities in the Nordic countries since 2017, carried out by Chen et al. (2021a). In addition, we have incorporated assumptions from some newer studies (Energistyrelsen, 2020; NVE, 2020).

Table 5 shows a relatively large variation in the assumptions for major price drivers used in earlier power market outlook studies. For instance, assumed wind power capacities in the Nordic countries in 2040 ranged from 25 GW to 82 GW (Chen et al., 2021a). Similarly, generation capacities in Norway varied between 39 and 68 GW in 2040. Nordic demand projections vary between 409 and 680 TWh in 2040, where 7%–9% will be from electrical vehicles. Industrial demand represents about half of the consumption, including data centres and hydrogen production. We assume that the average values found from the literature review represent the most likely values and we assume a triangular probability distribution for generation capacity and demand. For generation capacity in the Nordic countries, the value is included exogenously in the model simulations, according to the sampling strategy, but we allow the solver to distribute the capacities between different regions within each country.

The range of technology costs is based on Energistyrelsen (2020), and implemented as a change from the base values in Balmorel. Fuel price uncertainty is based on Chen et al. (2021a), but fuel price of biomass is based on extrapolation of historical variations from Energimyndigheten (2020).

All the parameters shown in Table 5 are included in the Morris screening, whereas the subsequent Monte Carlo simulations include the twenty most important factors found by the Morris screening.

3. Results

In this chapter we present the main results of the investigation. The first section (3.1) identifies the main price drivers using the Morris screening method, whereas Section 3.2 describes the sensitivity of the price to these main drivers, quantified using the Monte Carlo procedure. Section 3.3 presents the price and revenue risk shown by the Monte Carlo simulations, whilst Section 3.4 presents the results on the market values of renewable power generation.

3.1. Main price drivers and their risks - Morris sampling

In the first step of our investigation, all of the relevant input parameters shown in Table 5 are included in the Morris sampling with $p = 8$ and $r = 15$, which give a step length of $\Delta = \frac{4}{7}$ and a total of 1050 model runs. Fig. 4 shows the average (μ) and standard deviation (σ) of the elementary effects for the each of the input parameters on the average electricity price in Norway. In general, a high average (μ) contributes to a high impact of the parameter compared to the input uncertainty range. A high standard deviation (σ) implies that the input parameter has high degree of interactions (non-linear effects) with other parameters. For example, the investment cost of onshore wind generation capacity (number 31 in the figure) has a relatively high average level and a low standard deviation. This indicates that onshore wind investment costs have a large impact on Norwegian electricity prices in 2040, but the impact is largely independent of the level of other input parameters. The natural gas price (66) has high average scaled elementary effects value and high standard deviation, suggesting both a large impact on the electricity prices and relatively strong interactions with at least one of the other parameters. Finally, the investment costs of natural gas generation capacity (35) induces variation in other parameters, but does not cause price variation by itself. The results from the Morris sampling procedure show that the three parameters with the largest impact on the electricity price in Norway in 2040 are the natural gas price (66), the carbon price (29), and onshore wind investment costs (31).

3.2. Estimated impact of the main parameters

In this section, we consider in greater detail the impacts of the main input parameters from the sensitivity analysis based on the Morris method. Table 6 summarizes the results for the main parameters identified by the method, whereas Table 7 and Table 8 in the appendix provide additional details. The tables show the minimum, maximum, and average impact on the average annual electricity price in 2040, for the parameters that were identified as the most influential. The impact is based on the difference between two scenarios where the only difference is in that particular parameter, according to eq. 1. This is repeated several times, for different values of the remaining parameters. A positive elementary effect means that an increase in the input parameter causes an increase in electricity prices, whereas a negative elementary effect means that an increase in the input results in lower electricity prices. The results show that both supply side and demand side drivers are among the main price drivers, and that both domestic and international drivers will affect the Norwegian electricity prices in 2040.

3.2.1. Generation capacity

The price effect of increasing the installed capacity in Norway is between −0.03 €/MWh and − 0.69 €/MWh per GW of additional capacity, depending on the technology. The highest price sensitivity is observed for increased capacity of highly flexible hydropower plants. The lowest price impact is found for solar PV capacity, which is both intermittent and primarily produces during the summer, which is the low demand season in Norway. Increased wind power capacity affects prices somewhat less than hydropower (on average − 0.3 €/MWh per GW capacity increase).

The results show that Norwegian power prices are also sensitive to capacity changes in neighbouring countries. The average price impact of Swedish nuclear power generation capacities is similar to that of Norwegian hydropower (−0.44 €/MWh per GW). We also notice that Finnish nuclear capacity is an important driver for Norwegian prices. Also, hydropower and wind power capacities in Sweden have relatively large impacts, with average values of −0.30 €/MWh per GW and − 0.20 €/MWh per GW, respectively. The wind power capacities in Finland and Denmark, and nuclear capacity in France and the UK, have limited impacts on Norwegian prices.

3.2.2. Demand

The model simulations show that domestic electricity consumption increases the power price by 0.03–0.18 €/MWh per increased TWh. The corresponding price effect of increased consumption in other Nordic countries is somewhat lower, with a price effect between −0.05 and 0.10 €/MWh per TWh. The price impact is larger for inflexible demand, like power-intensive industries, than for flexible demand, like EV charging.

3.2.3. Carbon price

An increase in the carbon price of 1 €/tonne CO_2 causes an increase in the 2040 Norwegian power prices of up to 0.10 €/MWh, with an average increase of 0.04 €/MWh. The highest impacts are observed in cases where the electricity prices are relatively low. The Norwegian generation mix is not directly affected by the carbon price, since no fossil fuel is used for power generation. Instead, prices are affected indirectly through increased costs of fossil generation and increased renewable investments abroad. Increased carbon prices cause an increase in the cost of importing electricity, as well as increased export of flexible Norwegian hydropower. This increases the value of transmission lines, but it also increases the Norwegian power prices.

3.2.4. Fuel prices

The Morris sampling suggests a significant impact of the natural gas price, even in 2040. On average, we find a sensitivity of 0.75 €/MWh for a gas price increase of 1 €/GJ. The corresponding minimum and maximum impacts are −0.08 and 1.5 €/MWh. The natural gas price sensitivity varies depending on the assumed carbon price, since natural gas generation is more competitive and is therefore the price setting technology for more hours when the carbon price is low. Apart from natural gas, the other fuel prices – coal, fuel oil, pellets, and wood chips – were found to have minor impacts on Norwegian prices in 2040.

3.2.5. Investment, operation and management costs, and technological efficiency

We find that the investment costs in wind and solar power have a small positive impact on Norwegian power prices. Similarly, the cost of technologies that increase electricity consumption, such as heat pumps, have negative impacts. The effects of waste incineration plants investment costs are not significant. Similarly, operation and management costs and technological efficiency were found to have a minor impact on power prices.

3.2.6. Seasonal differences in the price impacts

Some parameters influence the electricity prices differently in the different seasons (Fig. 5 and Table 8). In particular, Fig. 5 shows that the natural gas and carbon prices have a significant positive impact on electricity prices in the heating season (weeks 4 and 43), but a relatively large negative impact on electricity prices outside the heating season (weeks 17 and 30). In addition, wind power generation capacities and investment costs have smaller price impacts during the winter (week 4) than otherwise.

Firstly, this indicates that natural gas is more often the marginal producer during the heating season, such that fluctuations in the generation costs of natural gas price have a greater impact on the electricity price during the heating season. Secondly, the negative price impact of natural gas generation costs outside the heating season suggests that a high natural gas generation cost may lead to higher investments in wind and solar generation capacity, which results in lower electricity prices in the summer season with low overall consumption. This explanation is consistent with the lower price impact of wind power generation capacities and investment costs during the winter than during the summer. That is, high costs of natural gas-fired generation affect the deployment of renewables, although natural gas remains the main marginal producer during the winter. During the summer, however, renewables more frequently become the marginal producer, increasing the price impact of the factors related to wind power during the summer.

3.3. Price and revenue risks

After identifying the main factors affecting the electricity price using the Morris sampling method, we ran Monte Carlo simulations to provide a more precise quantification of their impacts. We performed 3632 independent model simulations with a Latin hypercube size of 20, including the 20 most important input parameters identified by the Morris screening (the parameters shown in Table 6).

The Monte Carlo simulations allow us to estimate the probability distributions of the Nordic power prices in 2040 (Fig. 6). As shown in Fig. 6, the Norwegian average annual power price ranges from 22.6 €/MWh to 50.1 €/MWh, with an average price of 39.6 ± 3.7 €/MWh. The corresponding Swedish price averages 42.1 ± 3.9 €/MWh and Danish and Finnish average prices are at 43.7 ± 3.3 €/MWh and 47.2 ± 4.4 €/MWh, respectively. The modelled price distributions fit relatively well to normal distribution curves.

3.4. Market values

Hirth (2013) and Tveten et al. (2016) identified large differences between average market prices and prices received by certain technologies, the so called market values, in future renewable-based energy systems. These existence of such large differences is supported by the probabilistic approach applied in this study. Fig. 7 shows histograms of the market values of wind power, hydropower, and solar PV from the Monte Carlo simulations, plotted with the 2040 levelized cost of electricity (LCOE). The LCOE estimates are based on a review of recent studies from Northern Europe including (Capros et al., 2016; DNV GL, 2020; Energistyrelsen, 2021; Entso-E, 2020; Fraunhofer, 2021; IEA, 2019; IEA, 2020; IEA, 2021; NVE, 2021a; Statnett, 2020). In these studies, LCOE estimates for offshore wind are in the range 25–73

Table 6
The minimum, maximum, and average price effects of the 20 most important input parameters. Prices refer to Norwegian yearly average. Unit: €/MWh/unit. An asterisk (*) indicates that the number is not significant different from zero at a 95% confidence level. The full table is shown in appendix (Table 7).

		Min	Average	Max	#
Capacity [GW]	Norway – Hydro	−0.69	−0.45	−0.24	1
	Norway – Onshore wind	−0.49	−0.34	−0.19	2
	Norway – Offshore wind	−0.53	−0.31	−0.10	3
	Sweden – Nuclear	−0.69	−0.44	−0.20	5
	Sweden – Hydro	−0.63	−0.30	−0.17	6
	Sweden – Onshore wind	−0.33	−0.20	−0.08	7
	Finland – Nuclear	−0.86	−0.30	−0.09	12
	UK – Nuclear	−0.24	−0.10	−0.02	16
Demand [TWh]	Norway – Residential	0.04	0.09	0.14	17
	Norway – Power intense industry	0.06	0.10	0.18	18
	Norway – EV	0.03	0.09	0.15	19
	Sweden – Power intense industry	0.03	0.06	0.10	21
Carbon Price [€/tonne]		−0.01	0.04	0.10	29
Investment cost [%]	Onshore wind	0.05	0.08	0.10	31
	Offshore wind	0.00	0.04	0.15	32
	PV	0.04	0.05	0.07	34
	Heat pump	−0.04	−0.02	−0.01	40
Operation and management cost [%]	PV	0.01	0.02	0.03	47
Efficiency [%]	Natural gas	−0.17	−0.07	0.03	57
Fuel prices [€/GJ]	Natural gas	−0.08	0.75	1.50	66

We find the market value for regulated hydropower to be 52 ± 6 €/MWh, which is 13 €/MWh higher than the average Norwegian power price. This corresponds to a value factor of 1.34,[4] illustrating the high value of the flexibility provided by the regulated hydro power plants. The market value of Norwegian hydropower is driven by the same parameters as the average Norwegian electricity prices, which is unsurprising since hydropower represents approximately 75% of the total Norwegian electricity production. The average market value for onshore wind in Norway is 32 ± 4 €/MWh, corresponding to a value factor of 0.80. The market value for onshore wind is close to the expected LCOE indicating that onshore wind may be profitable without subsidies, especially at sites with good wind conditions. The market value for offshore wind power (33 ± 3 €/MWh) is, however, below the average LCOE in the large majority of the simulations. Hence, with our assumptions, offshore wind is likely to need subsidies to be deployed in large scale in 2040. Solar PV has an average market value as low as 20 ± 3 €/MWh. Despite low LCOE estimates, solar PV does not look like an attractive option for the future Norwegian power market, given our model assumptions.

The initial Morris screening showed that market values for wind power were strongly affected by onshore wind investment costs in foreign regions, and the onshore wind power capacity in Norway and Sweden. This illustrates the so-called merit-order effect for wind power market values. In addition, the future nuclear power capacity in Sweden appears to have a substantial impact. The increase in the market value for wind power is driven by reduced generation capacity and increased onshore wind investment costs, since these factors drive the average electricity prices upwards. Increasing carbon prices do not contribute significantly to the PV market value, however, because the summer prices in Norway are mostly below SRMC of coal and gas power, and the carbon prices therefore do not affect the technology on the margin.

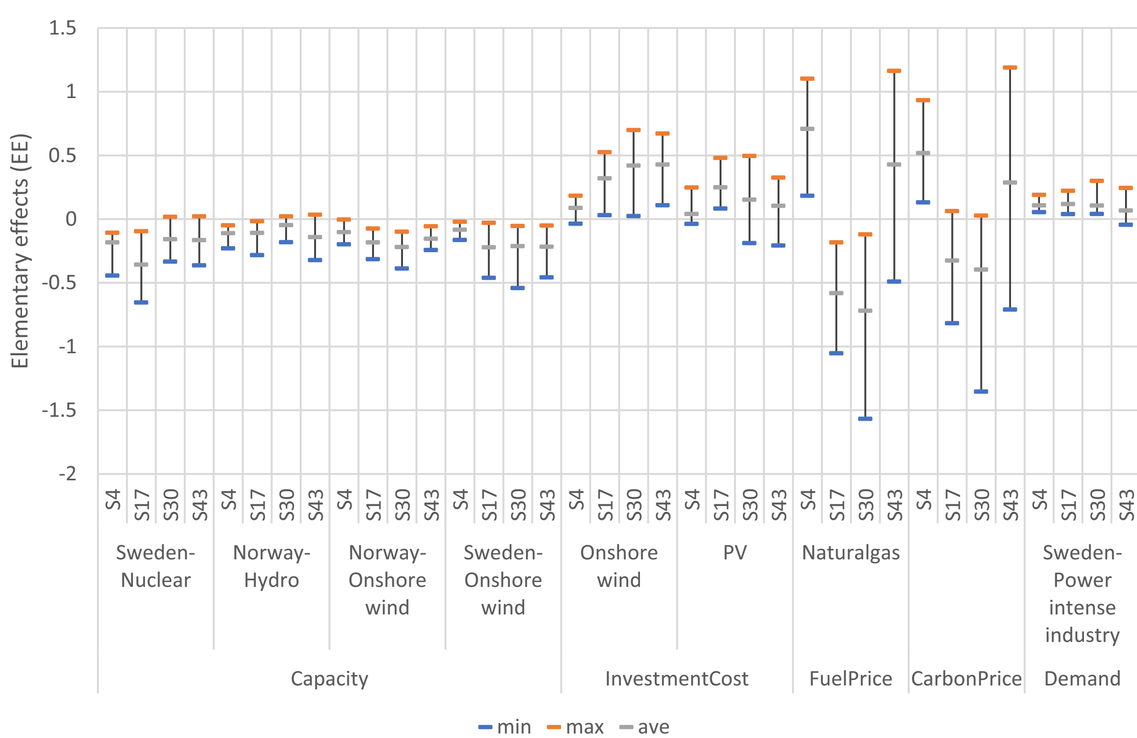

Fig. 5. Maximum, minimum, and average elementary effects for the individual weeks, only selected parameters are shown. For the weeks: S4 is representing winter, S17 spring, S30 summer, and S43 autumn.

€/MWh, with an average of 40 €/MWh. LCOE estimates for onshore wind are in the range 19–73 €/MWh, with an average of 32 €/MWh, and solar PV is in the range 20–63 €/MWh, with an average of 33 €/MWh.

[4] Value factor is defined as the market value of a specific technology divided by the market prices, for each hour.

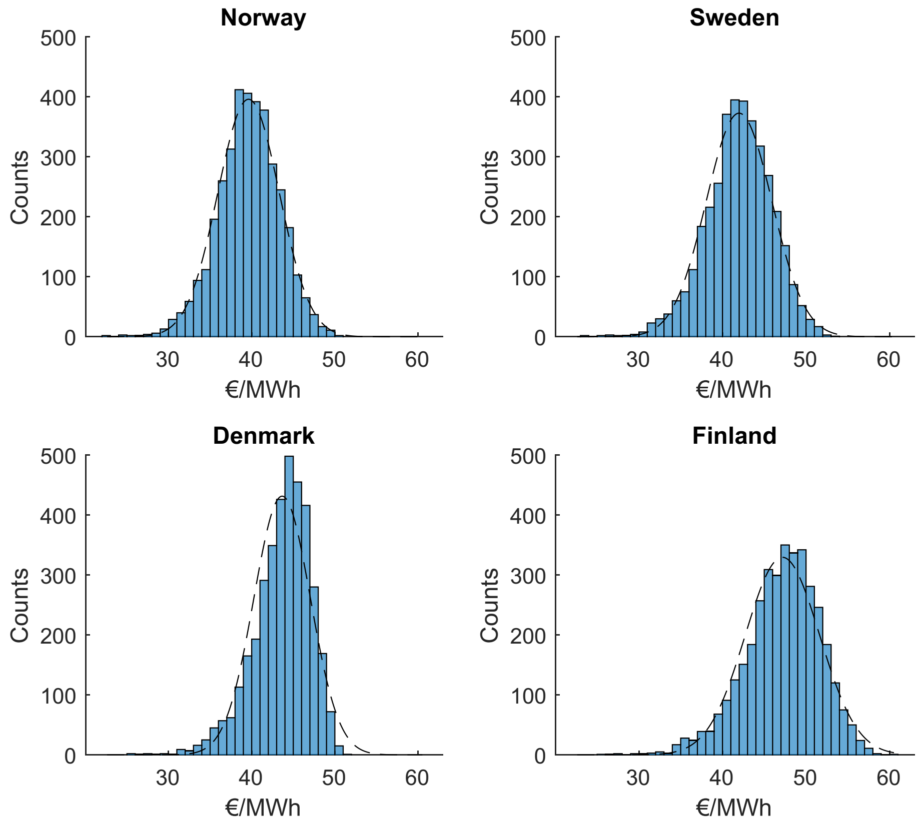

Fig. 6. Modelled price histogram of the weighted average yearly electricity price in the Nordic countries and normal distribution curve that best fit to the observed data (stippled line).

4. Discussion

This paper investigates the price impacts of a large number of uncertain factors on the Norwegian power market, but the findings are also relevant to other regions that are undergoing or planning a transition to renewable energy, in particular in Northern Europe. The large range of possible outcomes that we have found, due to uncertainty in the price drivers, shows how important it is to consider the underlying risks in studies that address the future energy transition. Although a global sensitivity analysis – such as the one we have conducted – increases the computational time, it provides important information about the uncertainties and risks in the modelled system, since it allows calculating nonlinear and interactive effects between the included factors. The Morris sampling procedure in our study, for instance, showed that the impact of the single most important factor we identified – the natural gas price – varies greatly, depending on the value of other variables. A normal one-at-a-time sensitivity analysis is unlikely to give a clear picture of the impacts of specific variables, since it would largely ignore interaction between different parameters. This study therefore highlights the importance of global sensitivity analysis in energy system modelling.

The estimated distributions of the market values for the different renewable technologies implies some large challenges for the transition to renewable energy sources. Although the average power prices are projected to increase, the market values of renewables suffer from the merit-order effect, both within Norway as well as the rest of North Europe. With the assumptions used in this study, market values of offshore wind and solar PV delivered to the Norwegian market are unlikely to exceed their LCOE, making them less attractive investments. Within the range of parameters considered in this study, large-scale deployment of these technologies may therefore not be commercially viable in Norway in 2040, such that some form of support would be necessary. This is a surprising result for the case of Norway, as earlier studies, such as by Brown and Reichenberg (2021), expect that the large flexibility available in regions dominated hydropower could dampen the merit-order effect. The finding in this study suggests that Norwegian power prices are likely to remain moderate and that summer price will be relatively low in the future North European power market. Onshore wind is more likely to exceed its LCOE – its market value exceeded the mean LCOE in 50% of the simulations.

On the other hand, however, Brown and Reichenberg (2021) show that increasing the carbon price can compensate for the merit-order effect on average, thereby allowing a high share of renewables in the system without causing cannibalisation. However, the high importance of carbon prices we found in our analysis suggests that such an increase in carbon prices would cause a large increase in electricity prices in Norway. It is also apparent that the necessary increase in carbon prices would be far higher than the carbon price expected for 2040 in market outlook studies, which all fell in the range between 10 and 130 €/tonne (Chen et al., 2021a).

Previous studies have also found the natural gas price to be among the most important factors for the system cost (Pye et al., 2015). Our results support the importance of the natural gas price as a price driver, even when the renewable share is high. Furthermore, our results show that the sensitivity of the electricity price to the natural gas price varies greatly with the values of other parameters, and over the year. Pizarro-Alonso et al. (2019) and Moret et al. (2017) found that investment costs are important for the Danish and the world energy system, which is consistent with our results for Norway. In general, our importance ranking of the factors appears to be consistent with the literature, although some differ with respect to the importance of biomass prices and availability: Pye et al. (2015) and Bosetti et al. (2015) both estimate that biomass is important in the UK and the US, whereas we rank biomass prices as the 35th most important factor, and insignificant for

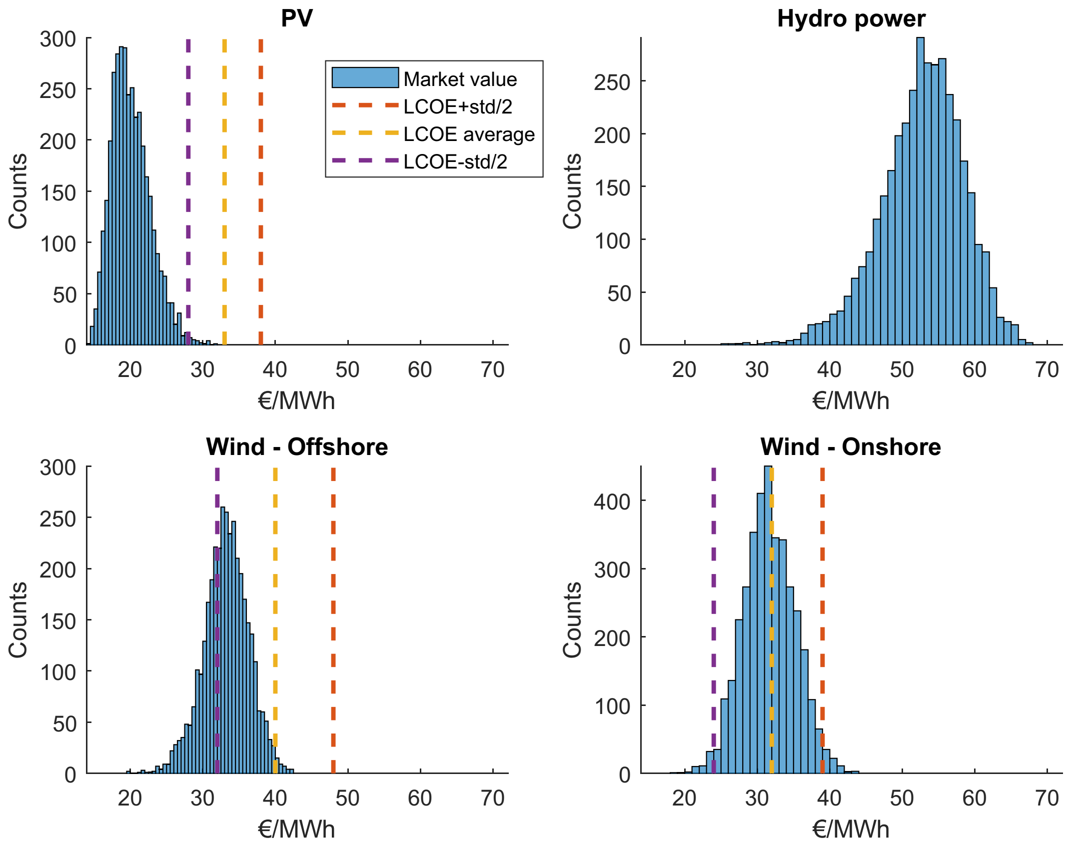

Fig. 7. Histogram of the modelled Norwegian market value in 2040, with the average and a half standard deviation away from average for LCOE the different technologies based on (Capros et al., 2016; DNV GL, 2020; Energistyrelsen, 2021; Entso-E, 2020; Fraunhofer, 2021; IEA, 2019; IEA, 2020; IEA, 2021; NVE, 2021a; Statnett, 2020).

the electricity price. This is likely due to the limited use of biomass for electricity generation in Norway compared with other countries.

The ranges and probability distributions of the price drivers in this study are based on reports and studies from the period between 2013 and 2021. However, in late 2021 and early 2022, fossil fuel and emission rights prices have increased beyond historical ranges and beyond most earlier expectations. In this perspective, some of the upper and lower bounds we have used in this study may seem too narrow. On the other hand, our approach takes a long-term perspective, where the fuel and carbon price assumptions should be interpreted as long term equilibrium prices. In either case, the market developments in late 2021 and early 2022 clearly demonstrate the need for including uncertainty in long term power market analysis.

5. Conclusion

In this study, we have ranked the price drivers of Norwegian electricity prices in 2040 by importance, and quantified the impacts of the main drivers on electricity prices and renewable market values. We found that natural gas and carbon emission rights prices will remain the main price drivers towards 2040, despite a substantial decline in natural gas in the North European power mix. In addition, the investment costs of onshore wind and the nuclear power capacity in Sweden are important factors for the long-term power price. In general, we found international markets and polices to be more important than domestic factors for the Norwegian power prices.

Monte Carlo simulations suggest an average Norwegian power price of 39 ± 4 €/MWh in 2040, and unlikely to slip below 23 €/MWh or exceed 50 €/MWh in normal weather years. Our results show that regulated hydropower will have a substantially higher market value than the average power price (value factor of 1.3–1.4). The corresponding value factors for wind and solar power were estimated to 0.8 and 0.5. The estimated market value of onshore wind power exceeds the estimated average LCOE from the literature in 50% of the simulations, whereas the market values of solar PV and offshore wind power only exceeded LCOE in 1% of the simulations. Thus, our results suggest that solar PV and offshore wind are unlikely to be commercially viable technologies in Norway in 2040, which raises serious concerns for the transition to renewable energy and implies that market intervention may be necessary.

Although this study has included a larger scope of uncertain drivers than earlier studies, recent events of the late 2021 and early 2022 have made it obvious that geopolitical factors should have been included in our analysis. We do not believe that recent events directly invalidate the insights of this study, but it is clear that they have profoundly altered the course of the European energy sector, and it would be interesting to update the analysis in light of recent events – updating both the probability distributions of the input parameters, and the including additional risk factors that, in hindsight, should be part of future studies. Further work is also needed to investigate how other developments in the energy sector will affect risk in the Norwegian power market, for instance related to sector coupling, the electrification trend, hydrogen production, weather and lack of social acceptance for certain technologies.

However, beyond increasing the number of price drivers and updating their probability distributions, we believe that the insights from our study provide a solid foundation for starting to design policies and mechanisms that will contribute to the renewable energy transition.

Data availability

The dataset and model used in this study can be found at https://gith ub.com/balmorelcommunity.

CRediT authorship contribution statement

Eirik Ogner Jåstad: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ian M. Trotter:** Conceptualization, Supervision, Validation, Writing – original draft, Writing – review & editing. **Torjus Folsland Bolkesjø:** Conceptualization, Funding acquisition, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

None.

Acknowledgments

Funding for this study was provided by the Norwegian Research Council through the 'Enabling the green transition in Norway' [NRF-308789] and 'Developing the Norwegian Energy System in the European Energy Transition' [NRF-280987]. This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.

Appendix A. Appendix

Table 7
The minimum, maximum, and average price effects of the different uncertainty input parameters with numbers used in figures. Prices refer to Norwegian yearly average. Unit: €/MWh/unit. An asterisk (*) indicates that the number is not significant different from zero at a 95% confidence level.

		Min	Average	Max	#
Capacity Norway [GW]	Hydro	−0.69	−0.45	−0.24	1
	Onshore wind	−0.49	−0.34	−0.19	2
	Offshore wind	−0.53	−0.31	−0.10	3
	PV	−0.15	−0.07	−0.03	4
Capacity ROW [GW]	Sweden – Nuclear	−0.69	−0.44	−0.20	5
	Sweden – Hydro	−0.63	−0.30	−0.17	6
	Sweden – Onshore wind	−0.33	−0.20	−0.08	7
	Sweden – Offshore wind	−0.44	−0.18	−0.02	8
	Sweden – PV	−0.08	−0.04	−0.02	9
	Denmark – Onshore wind	−0.16	−0.08	−0.04	10
	Denmark – Offshore wind	−0.17	−0.09	−0.02	11
	Finland – Nuclear	−0.86	−0.30	−0.09	12
	Finland – Onshore wind	−0.22	−0.10	0.01	13
	Finland – Offshore wind	−0.26	−0.09	−0.01	14
	France – Nuclear	−0.06	−0.04	0.00	15
	UK – Nuclear	−0.24	−0.10	−0.02	16
Demand Norway [TWh]	Norway – Residential	0.04	0.09	0.14	17
	Norway – Power intense industry	0.06	0.10	0.18	18
	Norway – EV	0.03	0.09	0.15	19
Demand Nordic [TWh]	Sweden – Residential	0.02	0.05	0.08	20
	Sweden – Power intense industry	0.03	0.06	0.10	21
	Sweden – EV	0.01	0.04	0.07	22
	Denmark – Residential	0.00	0.02	0.05	23
	Denmark – Power intense industry	0.00	0.02	0.04	24
	Denmark – EV	−0.05	0.00*	0.02	25
	Finland – Residential	0.00	0.02	0.04	26
	Finland – Power intense industry	0.01	0.03	0.05	27
	Finland – EV	−0.01	0.01	0.04	28
Carbon price [€/tonne]	Carbon Price	−0.01	0.04	0.10	29
Investment costs [%]	Waste	−0.02	0.00*	0.00	30
	Onshore wind	0.05	0.08	0.10	31
	Offshore wind	0.00	0.04	0.15	32
	Solar - collectors	0.00	0.00	0.00	33
	PV	0.04	0.05	0.07	34
	Natural gas	−0.02	0.01	0.04	35
	Pell - CHP	0.00	0.00*	0.04	36
	Pell – Heat only	0.00	0.00*	0.00	37
	Chips – CHP	0.00	0.01	0.05	38
	Chips – Heat only	0.00	0.00*	0.00	39
	Heat Pump	−0.04	−0.02	−0.01	40
	Natural gas – Heat only	0.00	0.00*	0.00	41
	Biogas	0.00	0.00*	0.00	42
Operation and management costs [%]	Waste	0.00	0.00*	0.00	43
	Onshore wind	0.00	0.01	0.03	44
	Offshore wind	0.00	0.01	0.04	45
	Solar collectors	0.00	0.00*	0.00	46
	PV	0.01	0.02	0.03	47
	Natural gas	0.00	0.01	0.02	48
	Pell – CHP	0.00	0.00*	0.02	49
	Pell – Heat only	0.00	0.00*	0.00	50
	Chips – CHP	0.00	0.00*	0.01	51
	Chips – Heat only	0.00	0.00*	0.00	52
	Heat Pump	−0.01	−0.01	0.00	53
	Natural gas – Heat only	0.00	0.00*	0.00	54

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Table 7 (*continued*)

		Min	Average	Max	#
	Biogas	0.00	0.00	0.00	55
Change in efficiency [%]	Waste	−0.01	0.00	0.00	56
	Natural gas	−0.17	−0.07	0.03	57
	Pell – CHP	−0.02	0.00*	0.00	58
	Pell – Heat only	0.00	0.00*	0.00	59
	Chips – CHP	−0.12	−0.01*	0.00	60
	Chips – Heat only	0.00	0.00	0.00	61
	Heat pump	−0.02	0.02	0.04	62
	Natural gas – Heat Only	0.00	0.00*	0.00	63
	Biogas	0.00	0.00	0.00	64
Fuel price [€/GJ]	Coal	0.00	0.13	0.57	65
	Natural gas	−0.08	0.75	1.50	66
	Fuel oil	−0.01	0.00	0.00	67
	Chips	−0.01	0.15*	1.10	68
	Pell	−0.01	0.00*	0.00	69

Table 8
The minimum, maximum, and average price effects of the different uncertainty input parameters for a representing winter week and summer week. Prices refer to Norwegian yearly average. Unit: €/MWh/unit. An asterisk (*) indicates that the number is not significant different from zero at a 95% confidence level.

		Winter week (S4)			Summer week (S30)		
		Min	Average	Max	Min	Average	Max
Capacity Norway [GW]	Hydro	−1.58	−0.75	−0.33	−0.29	−0.08	0.04
	Onshore wind	−1.2	−0.62	−0.02	−0.56	−0.31	−0.14
	Offshore wind	−1.09	−0.68	−0.27	−0.69	−0.21	−0.05
	PV	−0.19	−0.07	−0.01	−0.18	−0.11	−0.08
Capacity ROW [GW]	Sweden – Nuclear	−1.85	−0.76	−0.45	−0.33	−0.16	0.02
	Sweden – Hydro	−2.26	−0.81	−0.35	−0.28	−0.11	0.01
	Sweden – Onshore wind	−0.39	−0.20	−0.05	−0.31	−0.12	−0.03
	Sweden – Offshore wind	−0.58	−0.21	0.11	−0.25	−0.10	−0.01
	Sweden – PV	−0.11	−0.03	0.04	−0.08	−0.03	0.0
	Denmark – Onshore wind	−0.27	−0.07	0.10	−0.15	−0.06	0.02
	Denmark – Offshore wind	−0.32	−0.03*	0.18	−0.15	−0.07	−0.01
	Finland – Nuclear	−1.95	−0.38	0.24	−0.38	−0.15	0.01
	Finland – Onshore wind	−0.32	−0.08	0.07	−0.23	−0.05	0.02
	Finland – Offshore wind	−0.21	−0.03*	0.20	−0.18	−0.04	0.12
	France – Nuclear	−0.29	−0.08	0.05	−0.08	0.0*	0.10
	UK – Nuclear	−0.54	−0.16	−0.03	−0.14	−0.03*	0.03
Demand Norway [TWh]	Norway – Residential	0.07	0.14	0.26	0.0	0.02	0.05
	Norway – Power intense industry	0.07	0.17	0.29	0.02	0.05	0.09
	Norway – EV	−0.18	0.04*	0.20	−0.05	0.04	0.17
Demand Nordic [TWh}	Sweden – Residential	0.05	0.10	0.27	−0.01	0.02	0.05
	Sweden – Power intense industry	0.07	0.13	0.24	0.01	0.03	0.09
	Sweden – EV	−0.01	0.04	0.13	−0.01	0.01	0.06
	Denmark – Residential	−0.03	0.04	0.17	−0.01	0.01	0.02
	Denmark – Power intense industry	0.0	0.03	0.07	0.0	0.01	0.02
	Denmark – EV	−0.09	0.0*	0.15	−0.05	−0.01	0.01
	Finland – Residential	−0.03	0.06	0.40	−0.01	0.01	0.03
	Finland – Power intense industry	−0.02	0.03	0.09	−0.01	0.02	0.05
	Finland – EV	−0.09	0.02*	0.19	−0.03	0.0*	0.02
Carbon price [€/tonne]	Carbon Price	0.05	0.18	0.32	−0.11	−0.03	0.0
Investment costs [%]	Waste	0.0	0.0*	0.02	0.0	0.0*	0.0
	Onshore wind	−0.02	0.06	0.12	0.0	0.06	0.11
	Offshore wind	−0.05	0.02*	0.13	0.0	0.04	0.16
	Solar - collectors	−0.01	0.0*	0.0	0.0	0.0*	0.0
	PV	−0.03	0.03	0.18	−0.03	0.03	0.09
	Natural gas	0.05	0.11	0.18	−0.05	−0.03	−0.01
	Pell - CHP	0.0	0.01*	0.18	−0.02	0.0*	0.0
	Pell – Heat only	0.0	0.0*	0.0	0.0	0.0*	0.0
	Chips – CHP	−0.03	0.01*	0.09	−0.05	0.0*	0.01
	Chips – Heat only	0.0	0.0*	0.0	0.0	0.0*	0.0
	Heat Pump	−0.12	−0.05	−0.02	0.0	0.02	0.03
	Natural gas – Heat only	0.0	0.0*	0.0	0.0	0.0*	0.0
	Biogas	0.0	0.0*	0.0	0.0	0.0*	0.0
Operation and management costs [%]	Waste	0.0	0.0*	0.0	0.0	0.0*	0.0
	Onshore wind	0.0	0.01	0.03	0.0	0.02	0.03
	Offshore wind	−0.03	0.01*	0.08	0.0	0.02	0.07
	Solar collectors	0.0	0.0*	0.0	0.0	0.0*	0.0
	PV	−0.02	0.03	0.10	0.0	0.01	0.05
	Natural gas	0.0	0.05	0.10	−0.03	−0.01	0.0
	Pell – CHP	0.0	0.0*	0.04	−0.01	0.0*	0.0
	Pell – Heat only	0.0	0.0*	0.0	0.0	0.0*	0.0

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Table 8 (*continued*)

		Winter week (S4)			Summer week (S30)		
		Min	Average	Max	Min	Average	Max
	Chips – CHP	−0.01	0.01*	0.05	−0.01	0.0*	0.0
	Chips – Heat only	0.0	0.0	0.0	0.0	0.0*	0.0
	Heat Pump	−0.02	−0.01	−0.01	0.0	0.0	0.01
	Natural gas – Heat only	0.0	0.0*	0.0	0.0	0.0*	0.0
	Biogas	0.0	0.0	0.0	0.0	0.0	0.0
Change in efficiency [%]	Waste	−0.01	0.0*	0.0	−0.01	0.0	0.0
	Natural gas	−0.63	−0.36	−0.03	0.0	0.07	0.16
	Pell – CHP	−0.09	−0.01*	0.0	0.0	0.0*	0.01
	Pell – Heat only	0.0	0.0*	0.0	0.0	0.0*	0.0
	Chips – CHP	−0.05	0.01*	0.24	−0.01	0.0*	0.0
	Chips – Heat only	0.0	0.0*	0.0	0.0	0.0*	0.0
	Heat pump	0.07	0.11	0.15	−0.06	−0.02	0.0
	Natural gas – Heat Only	0.0	0.0*	0.0	0.0	0.0*	0.0
	Biogas	−0.02	0.0*	0.01	0.0	0.0*	0.0
Fuel price [€/GJ]	Coal	−0.19	0.28	1.03	−0.27	−0.02*	0.07
	Natural gas	0.87	3.37	5.24	−1.76	−0.81	−0.13
	Fuel oil	−0.02	0.0*	0.01	−0.01	0.0*	0.01
	Chips	−0.10	0.19*	1.69	−0.27	−0.02*	0.09
	Pell	−0.03	0.0*	0.01	0.0	0.0*	0.01

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