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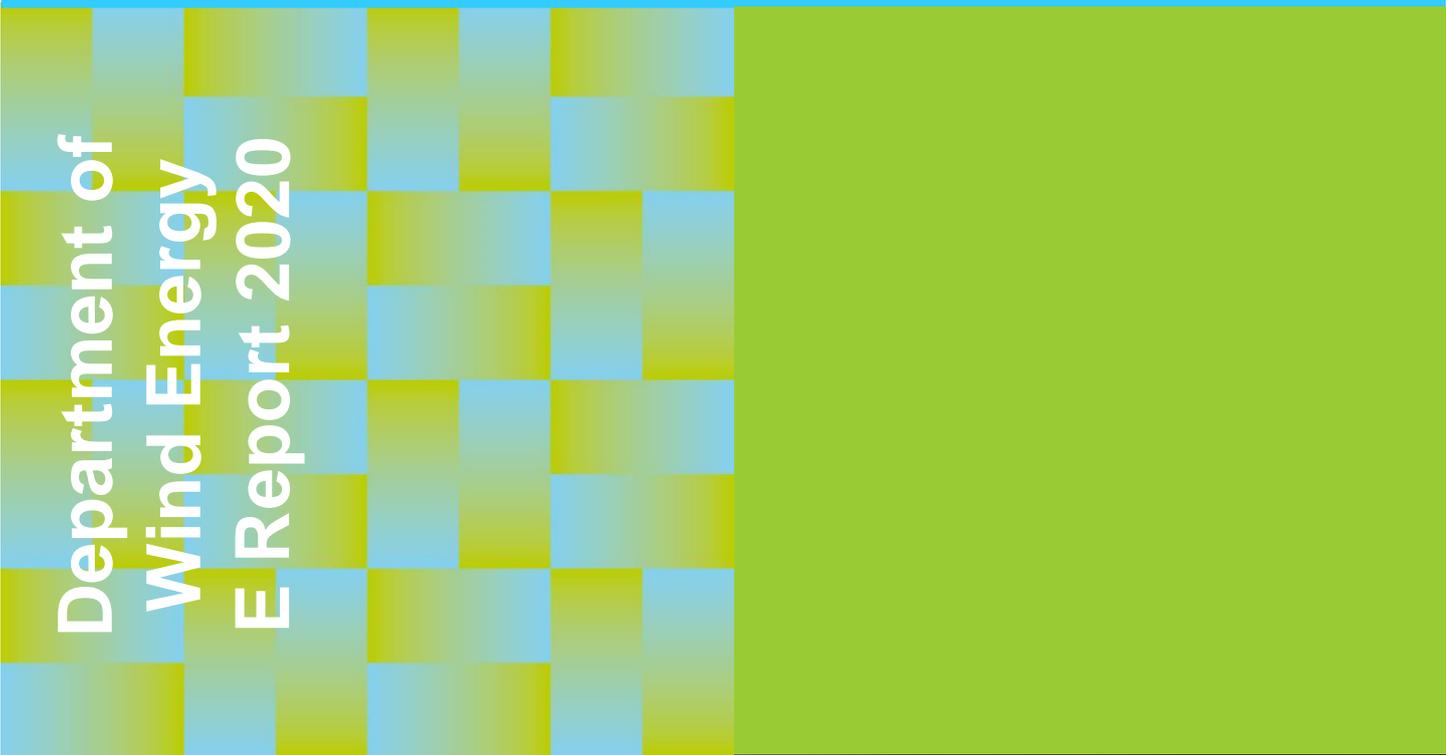
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Elia - MOG II System Integration – Public version



Department of Wind Energy E Report 2020

Poul Sørensen, Matti Koivisto and Juan Pablo Murcia

DTU Wind Energy E-0203

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Preface

This study has been performed as a consultancy contract between ELIA and DTU Wind Energy following the “MOG II System Integration” request by ELIA.

Roskilde, Denmark, May 2020

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Summary

This document is the final report of Elia's Consultancy project on MOG II System Integration.

The existing Belgian offshore fleet is one of the areas with the highest density installation of wind energy worldwide. This report studies the impact of the production variations and the forecast errors on the balancing of the Elia grid when extending the Belgium offshore fleet (MOG II project).

This report demonstrates the validation of DTU's CorWind model to capture the generation time series of the offshore wind power plants that were operating in Belgium beginning of 2018 (see chapter 6). It is thus considered valid for modelling the MOG II capacity extension.

The report documents the wind turbine technology trends and proposes installed capacity/technology scenarios for the MOG II wind energy fleet extension. The most important parameters for the purpose of this study are turbine specific power and hub height, and storm shutdown behaviour. Two different wind turbine specific powers are considered; a larger rotor with lower specific power (Technology B) produces larger capacity factors but is expected to represent higher cost turbines (compared to Technology A, with higher specific power). Three storm shutdown types are modelled and compared, with the "Deep" type providing least ramping during very high wind speeds. The "Moderate" type provides less reduction of ramping during high wind speeds compared to Deep.

The future wind plants increase the aggregated capacity factor of the fleet from BE 2018 towards the 4.4 GW scenarios, with Technology B showing significant increase compared to Technology A; this leads to more annual offshore generation with the same installed capacity despite of the additional wake losses from the new installations.

The standardized generation ramps are expected to be reduced towards the 4.4 GW of installations. This is caused by larger distances between plants (i.e., geographical smoothing). Fleet-level 5 min ramps are reduced more than 1 hour ramps. However, expressed in absolute power, ramps are expected to increase significantly in the future due to the larger capacity installed. In the 4.4 GW scenarios, ramps of more than 2 GW in 1 hour are expected to occur multiple times in a year. 1 hour down-ramp larger than 2.5 GW is expected approximately on one day in a year. Up-ramp of more than 2.5 GW in 1 hour is expected approximately on 2 or 3 days a year. Comparing high wind days (fleet-level mean wind speed > 20 m/s) and the rest of the days showed that most extreme ramps occur during high wind speed days, especially for 5 and 15 min ramps. However, an up-ramp larger than 4 GW within 1 hour was seen once in the simulation for non-storm days. This shows that very extreme ramps are possible on non-storm days, but they are unlikely. Even though similar size down-ramp was not seen in the simulations, it cannot be ruled out that such down-ramp events could not happen in the future.

It is possible to lose the full 4.4 GW of installed capacity in all studied 4.4 GW cases due to an extreme storm event. The number of years where this occurs is 6 or 7 out of the simulated 37 years for the 4.4 GW scenarios, depending on the technology scenario. Out of the 3 different storm protection technologies considered, the Deep storm shutdown type results in the lowest loss of power and in less fast (5 or 15 min) ramping during storms. The following numbers are for

the 4.4 GW scenarios. For 15 min ramps, > 2 GW down-ramps are seen in the simulations a few times over the 37 years for the regular 25 m/s direct cut-off storm shutdown type, but such event was not seen for scenarios with the Deep or Moderate type. The Deep type shows a reduction of down-ramps compared to Moderate: 15 min down-ramps of > 1 GW and > 1.5 GW are approximately half as likely for the Deep than for the Moderate type. 5 min down-ramps are also reduced: a 5 min down-ramp of > 0.5 GW is expected to occur on multiple days a year for the 25 direct cut-off, on 1 or 2 days a year for the Moderate and on less than one day a year for the Deep type.

For 1 hour ramps in the 4.4 GW scenarios on high wind days (fleet-level wind speed > 20 m/s), a down-ramp of more than 2 GW is expected to happen on a few days over a year with the 25 m/s direct cut-off type. For similar scenarios with the Deep type, such event is expected on less than one day a year. However, on the fleet-level (4 or 4.4 GW), the most severe 1 hour down-ramps are relatively similar for all storm shutdown types. On storm days, extreme up-ramps are more likely than similar size down-ramps; this is affected by the storm shutdown slowing only the shutdown and not the restart part of the power curve. Mitigation of such up-ramp events after storms should be considered as they represent some of the largest power fluctuation events.

Geographical smoothening is also expected to decrease aggregate forecast errors (in standardized generation). Large forecast errors are more likely during high wind speed days (max wind speed > 20 m/s). The Deep storm shutdown type shows slightly lower forecast errors during high wind speeds days compared to the other studied storm shutdown types.

Analysis of historical data from 2018-19 shows that the increasing capacity from 877 MW to 1548 MW of offshore wind power has increased the offshore wind power forecast errors in the Elia system. The analyses of correlation between offshore wind power and system imbalance show that the wind power forecast error is much more correlated with imbalance than the wind power production and forecast, meaning that the forecast errors is the main cause for imbalances, whereas the impact of wind power variability is mitigated by the spot market and intraday trading. This analyses also indicates that the correlation coefficients between wind power and system imbalance are generally increasing for increasing installed capacity, but this trend is not very significant.

Statistical analyses of the individual BRPs imbalances show significant differences in the statistical probability density functions of different BRPs. This indicates that there is a significant difference between BRPs in the way that they manage to handle the forecast errors.

Finally, the analysis of forecast error correlation with individual BRP imbalances, BRP sum imbalances and system imbalances also shows significant increase of the correlations between forecast errors and imbalances during days with high forecast errors, extreme ramping events and during storm events.

1. Introduction

The planned installed capacity of wind farms in the Belgian offshore area by the end of 2020 is approximately 2.3GW, see Table 1. In the Marine spatial planning 2020-2026, the Belgian minister competent for the North Sea has established the framework for an additional production zone of 281 km² (at the frontier with France), in addition to the wind zone of 225 km² which already exists (at the frontier with the Netherlands). This new zone will allow up to 2.1GW additional installed capacity. The assumption used is that this additional capacity will be commissioned between 2026 and 2028.

Name	MW	Manufacturer	Turbine model	Turbine MW	Rotor diameter m	ws_shutdown_begin	ws_shutdown_end	ws_restart_begin	ws_restart_end	Hub height m	Number of turbines	Commissioning year
Belwind	165.0	Known	Known	3.0	90	Based on measured data				Known	55	2010
Nobelwind	165.0	Known	Known	3.3	112	Based on measured data				Known	50	2017
Norther	370.0	Known	Known	8.4	164	Deep type				Known	44	2019
Northwester_2	218.5	Known	Known	9.5	164	Deep type				Known	23	2020
Northwind	216.0	Known	Known	3.0	112	Based on measured data				Known	72	2014
Rentel	308.7	Known	Known	7.4	154	Deep type				Known	42	2018
Seastar	252.0	Known	Known	8.4	164	Deep type				Known	30	2020
Mermaid	235.2	Known	Known	8.4	164	Deep type				Known	28	2020
C_Power_1	30.0	Known	Known	5.0	126	Based on measured data				Known	6	2009
C_Power_2	147.6	Known	Known	6.2	126	Based on measured data				Known	24	2012
C_Power_3	147.6	Known	Known	6.2	126	Based on measured data				Known	24	2013
Noordhinder Noord	Tech data depends on the scenario										2026	
Noordhinder Zuid	Tech data depends on the scenario										2026	
Fairybank	Tech data depends on the scenario										2026	

Table 1. Technical characteristic of the Belgian offshore wind power plants. For the existing OWPPs with measurements, turbine shut-down and restart wind speed limits are based on measured wind speed and generation data. OWPPs with hi-wind operation turbines are assumed to follow the “Deep” type shown in Figure 10 (other information was not available).

The objective of this study is to define the impact of the new wind parks on storm events, wind power ramping events and wind power forecast errors. An historical analysis of the impact of wind parks on system imbalance is performed in order to support Elia in defining the expected reactions

of BRPs once the additional capacity will be commissioned. The consequences for the grid as well as the definition of possible necessary mitigation measures are not included in the scope of this study.

The study is based on analysis of existing data focusing on the latest 2 years 2018-19 and on simulations of specified scenarios for the future offshore wind power in the existing and the new zones.

The report is structured as follows:

Chapter 2 describes the trends and selected wind turbine technologies relevant for the MOG II extension in 2026. This includes the general technical specifications of the turbines such as specific power, rated power, rotor diameter and hub height, as well as their power curves including storm protection operation.

Chapter 3 explains the root causes for ramping events and it uses measured ramp event examples on the operation of existing wind farms. This chapter shows that the main cause for ramping events is wind speed fluctuations.

Chapter 4 presents the scenarios studied in terms of installed capacity and of technology for the MOG II extension. It also includes the locations of the plants currently in operation used in model validation.

Chapter 5 describes the methodology used to simulate the operation of the plants in a given scenario. This includes description of CorWind, the core model for simulating the time series of wind energy production of a both large spatial scale and temporal length. Additionally, the methodologies for wake modelling and storm shutdown modelling are explained. Finally, Chapter 5 highlights the methodology for filtering generation measurements in order to represent future installed capacities.

Chapter 6 documents the model validation based on the generation and wind speed measurements from the currently operating plants. Validation results are detailed on both plant level and on aggregated (fleet) level for several variables such as capacity factors, wind speed, generation probability distributions, generation, correlations, ramps, probability density functions (PDFs) and ramp correlations. Additionally, this chapter presents the model validation in terms of storm shutdowns, high wind speed probabilities, and forecast errors for different forecast horizons.

Chapter 7 analyses the basic statistics of the results for all capacity/technology scenarios in terms of capacity factors, standard deviation of standardized generation and PDF of standardized generation.

Chapter 8 presents the statistical analysis of ramping events for several time periods (5 minutes, 15 minutes and 1 hour) in terms of standardized generation and in actual GW of power fluctuation. Additionally, this chapter compares ramp likelihoods for days without high wind speeds in order to dissociate ramp events due to wind variations from ramp events due to storm shutdowns. Finally, this chapter concludes and gives input for mitigation of ramps in section 8.5.

Chapter 9 introduces the methodology used for identification of storm events from the 37 years of simulated generation. Additionally, this chapter analyses the resulting statistics of frequency of occurrence of such events as a function of their severity for each installed capacity/technology scenario. This chapter gives conclusions and input for mitigation of storm-related ramp events in section 9.6.

Chapter 10 presents the statistical analysis of forecast errors in terms of standardized generation and in GW for the forecasting horizons currently used by Elia (Day-ahead, intraday and “Last”). Additionally, this chapter shows how the forecast errors change for days with large ramps or storm.

Chapter 11 analyses imbalances of individual balancing responsible parties (BRP) with offshore wind power, and at the system level. At system level, the sum of BRP imbalances and Elia’s system imbalance are analysed. The relationship between wind power and imbalances are presented, with special focus on the correlations between wind power forecast errors and imbalances, based on the data from real operation during the latest 2 years 2018-19.

2. Technological benchmark

The trends in offshore turbine technology are analysed in terms of turbine capacity, specific power and hub height. The trends combine the current turbines installed or planned in Belgium and the Netherlands, the Danish Energy Agency technology catalogue [1], and the prototype turbines from different manufactures currently being tested for certification. See Figure 1.

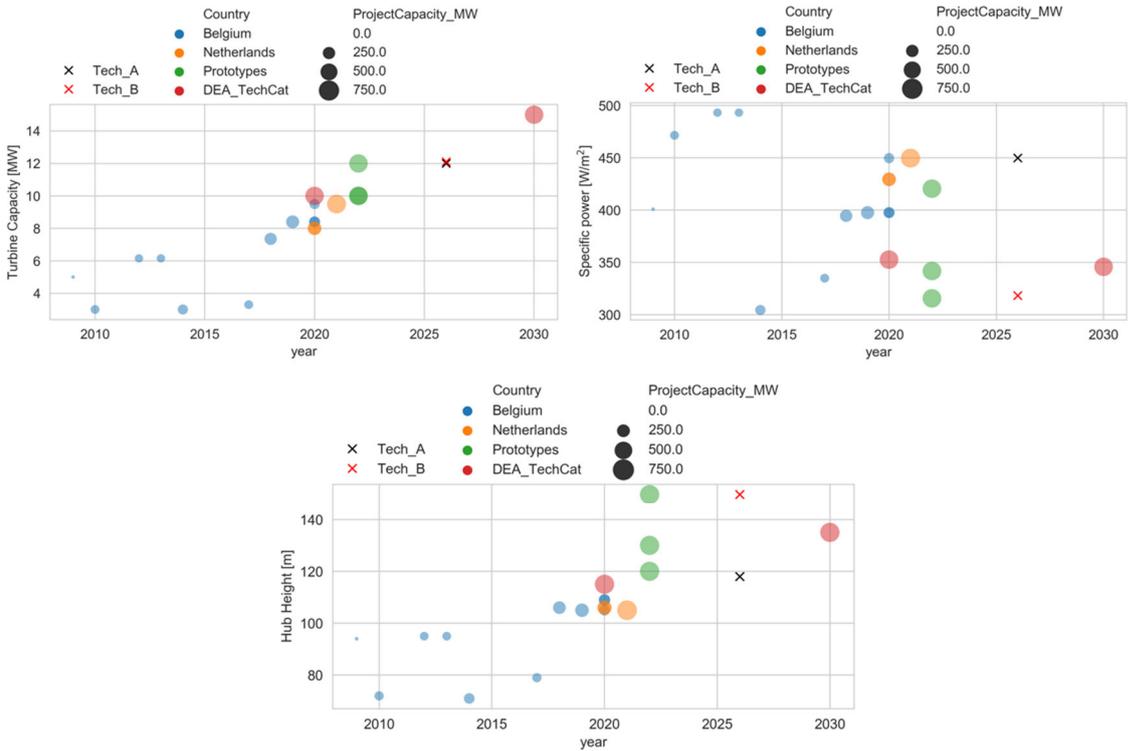


Figure 1. Trends in turbine capacity, specific power and hub height for offshore turbines.

Based on analyzing the trends from historical wind turbine data including prototype information online, two technology scenarios for the potential future offshore wind power plants (OWPPs) to be commissioned in 2026-28 are used. This study does not aim to use specific manufacturer technologies for those future wind turbines, but rather to make generic assumptions and supplement with sensitivity analyses where manufacturer differences and other uncertainties are considered important for the expected results regarding ramping and impact on system imbalance.

Two technology scenarios as listed in Table 2 have been validated by the stakeholders in the Elia workshop/meeting in Brussels the 23 January 2020. The two scenarios assume same rated power but different specific power (W/m²). We are aware that in reality, there will be a few MW range of rated power from different manufacturers, but we do not expect this difference in rated power to have significant impact on the results. From the available information about offshore wind turbine prototypes, we have observed significant differences in specific power which will impact power curves and thereby have possible impacts on ramp rates for wind speeds below rated. Given the

rated power, the different specific powers will influence the rotor diameter and the hub height as shown in Table 2.

Table 2. Technology scenarios for offshore wind turbines for additional installations

Technology scenario	A	B
Rated power	12 MW	12 MW
Rotor diameter	184 m	220 m
Hub height	118 m	150 m
Specific power	450 W/m ²	316 W/m ²

Those assumptions lead to the generic power curves shown in Figure 2 for the two technology scenarios, Tech A and Tech B. On top of this, based on manufacturer brochures and literature review, we propose three high wind technology scenarios also shown in Figure 2. For 25 direct cut-off, which is considered as baseline, the wind turbine will shut down when the 10 minute average wind speed exceeds 25 m/s. For HWS Moderate, the power will reduce for increasing wind speeds until the wind turbine shuts down at 28 m/s. Finally, for HWS Deep, the power will reduce for increasing wind speeds until the wind turbine shuts down at 31 m/s.

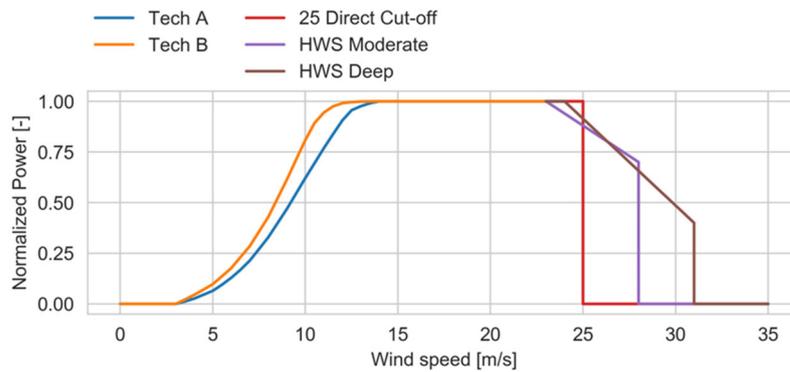


Figure 2. Power curves for assumed technology scenarios and storm shutdown scenarios.

Regarding storm shutdown and restart, we propose assumptions about the averaging time(s) and corresponding wind speed thresholds. In a previous study performed in the EU TWENTIES project, we assumed shutdown protections for averaging times 10 minutes (average), 30 seconds (gust) and 1 second (instantaneous). The corresponding wind speed thresholds increased for decreasing average times. We found from wind farm observations and from our simulations that a significant part of the turbine shutdowns were activated for all 3 average times.

The proposed generic wind turbine protection settings for the 3 high wind scenarios are shown in Table 3. As for the technology scenarios in Table 2, we are not aiming to use specific manufacturer technologies for those future wind turbines, but rather to make generic assumptions and supplement with sensitivity analyses where manufacturer differences and other uncertainties are considered important for the expected results regarding ramping during storm and resulting impact on system imbalance. So, the main purpose is to have the 3 major high wind shut down scenarios simulated to be able to compare them.

Table 3. Generic high wind turbine protection settings for the 3 high wind scenarios

Event	Averaging time	25 Direct Cut-off	HWS Moderate	HWS Deep
Shutdown	10 min	25 m/s	28 m/s	31 m/s
Shutdown	30 sec	28 m/s	31 m/s	34 m/s
Shutdown	1 sec	32 m/s	35 m/s	38 m/s
Restart	10 min	22 m/s	23 m/s	24 m/s

Finally, fast wind direction shifts could cause changes on the power because the power depends on the yaw error. However, provided that the yaw control dynamics is sufficiently fast – e.g. max 1 minute –the effect of yaw control is expected to be negligible in the studies looking at ramps at the wind farm level. Thus, yaw control dynamics are not considered in the simulations.

3. Root causes of ramping events

Wind farms are normally operated in a mode where the wind turbines generate maximum possible power. In this normal operation mode, changes in the power output from a wind farm (called “ramping events” in this study) occur continuously because of the variable nature of the wind field feeding the wind farm. However, since the wind farm power can be reduced below the available power as a consequence of control commands issued by the operator, ramping events also occur due to intentional control actions. This chapter describes only the root causes for ramping events during normal operation where the operator is not dictating ramps because of control commands.

Considering their expected frequency and the means available to manage them, root causes of ramping events below 300MW (out of the 4GW+ installed capacity) will not be analysed in detail by Elia. Therefore, this chapter will focus on identifying the root causes for ramping events above 300MW.

The main cause for ramping events is wind speed fluctuations. Even though the instantaneous (e.g. 1 second average) wind speeds differ significantly between wind turbines in a wind farm, the 1-5 minute averages are quite correlated, and as a result, the wind farm power can ramp significantly in 5 minutes. Another root cause for ramping events can be changes in wind direction. Such wind direction changes affect:

- The wake from upstream wind farms and the wakes inside the wind farm, which causes some ramping in the total wind farm power.
- When the change in wind direction is fast, yaw misalignment of the wind turbines is possible. However, since the wind turbine control systems adjust the yaw angle at least once in a minute and the wind direction changes take several minutes to affect all wind turbines, the yaw misalignment will not have significant impact on the total wind farm power.

Coming back to the main cause for ramping events, Figure 3 shows an example of wind farm power ramps affected by wind speed fluctuations around the steep part of the power curve. It is seen that 10th August in the evening between 22 and 23, the power decreases from full to less than half in less than one hour which is a result of a reduction in wind speed from approximately 13 m/s to approximately 8 m/s in the same period.

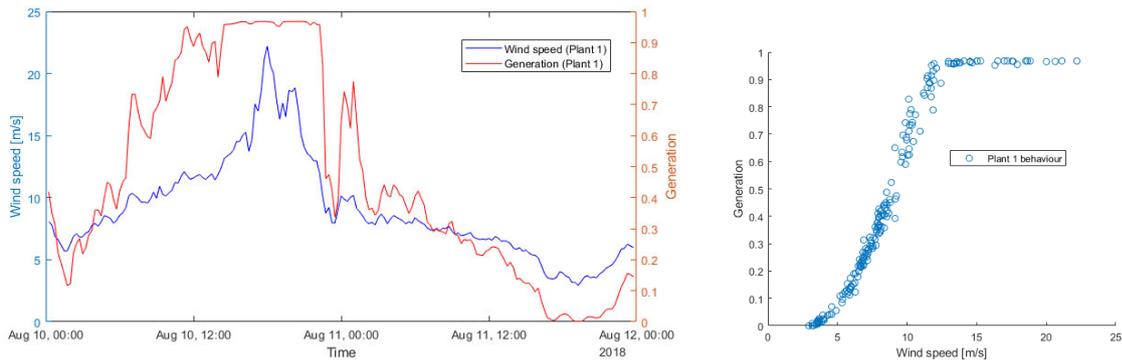


Figure 3. Example of power ramps from a single wind farm, affected by wind speed fluctuations around the steep part of the power curve.

For a single wind farm, such power reductions are often below the critical value of 300 MW, but with several offshore wind farms close to each other, the wind speeds are highly correlated, and therefore the total offshore wind power ramping can become significant.

The effect of strong correlation between wind power generated by two closely located wind farms is illustrated in Figure 4. It is seen that the second wind farm (Plant 2) reduces power even more on the 10th August in the evening, although this happens over a couple of hours. It is also noticed that the correlation between the two wind farm powers is 0.94, which is quite significant.

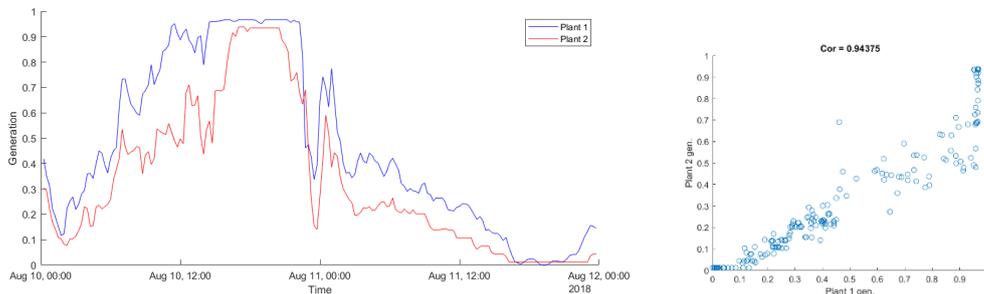


Figure 4. Example illustrating correlation between power ramps from two closely located wind farms.

Although the correlation between the two wind farm powers is quite significant, the correlation between fast ramp rates is relatively low. This is shown by the 15 minute ramp rates for the same case in Figure 5 where the correlation between ramp rates are only 0.17

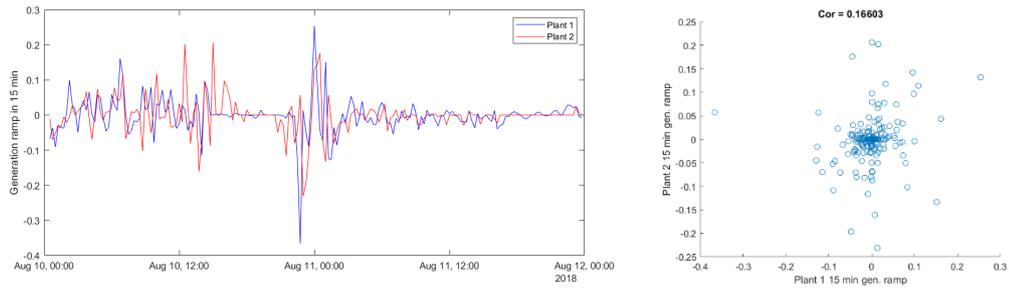


Figure 5. 15 minute ramp rates from two closely located wind farms.

A more extreme ramping event happened on the 15th October 2019. Figure 6 shows variations in wind speed measured at a single point together with power from 6 wind farms during the last 12 hours of that day. It is seen that the wind speed is quite stable until 20:00, but then the weather becomes more unstable, and especially between 21:30 and 22:00, there is a very significant spike in the wind speed, causing also the power from all wind farms to peak. Although this is not visible from the shown wind speed (measured at 43.96 m height on a single meteorological mast located on the MOG I platform), the spatial smoothing causes this wind speed spike to hit the wind farms at displaced times, which can be seen in the power from the individual wind farms. This example also illustrates that in extreme cases with very fast wind speed ramp rates, the spatial smoothing reduces the effect on total wind power significantly compared to the effect on the individual wind farms.

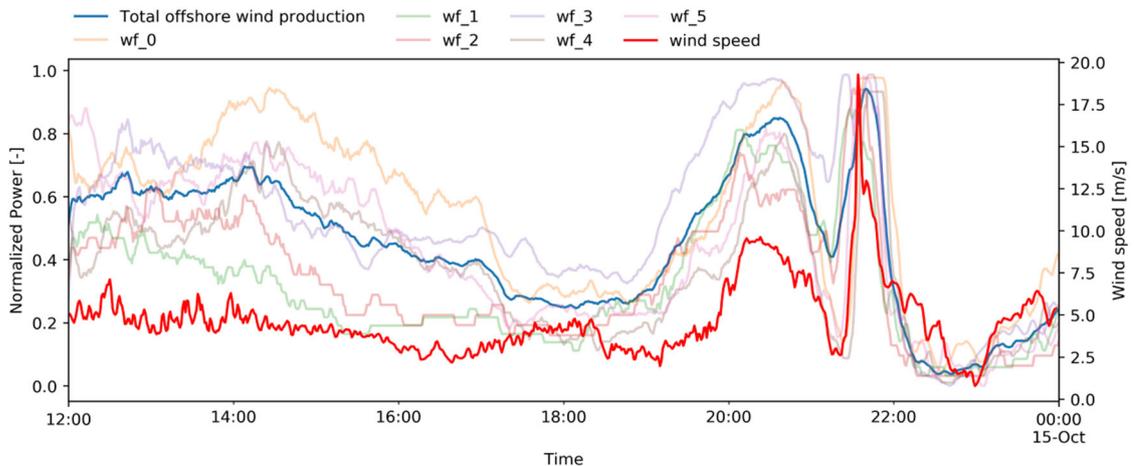


Figure 6. Wind speed and wind power from 6 wind farms 15th October 2019. Wind speed at 43.96m height above sea level from a single MET mast (WINDSNELHEID) located on the MOG platform.

4. Studied scenarios

This chapter starts by presenting the geographical positions of the Belgium OWPPs in the different studied scenarios. The first section shows the OWPPs used in CorWind model validation and Section 4.2 shows the OWPP installations scenarios towards a total offshore installation capacity of 4.4 GW in the Belgian offshore region. Figure 7 shows all the OWPPs considered in the entire study.

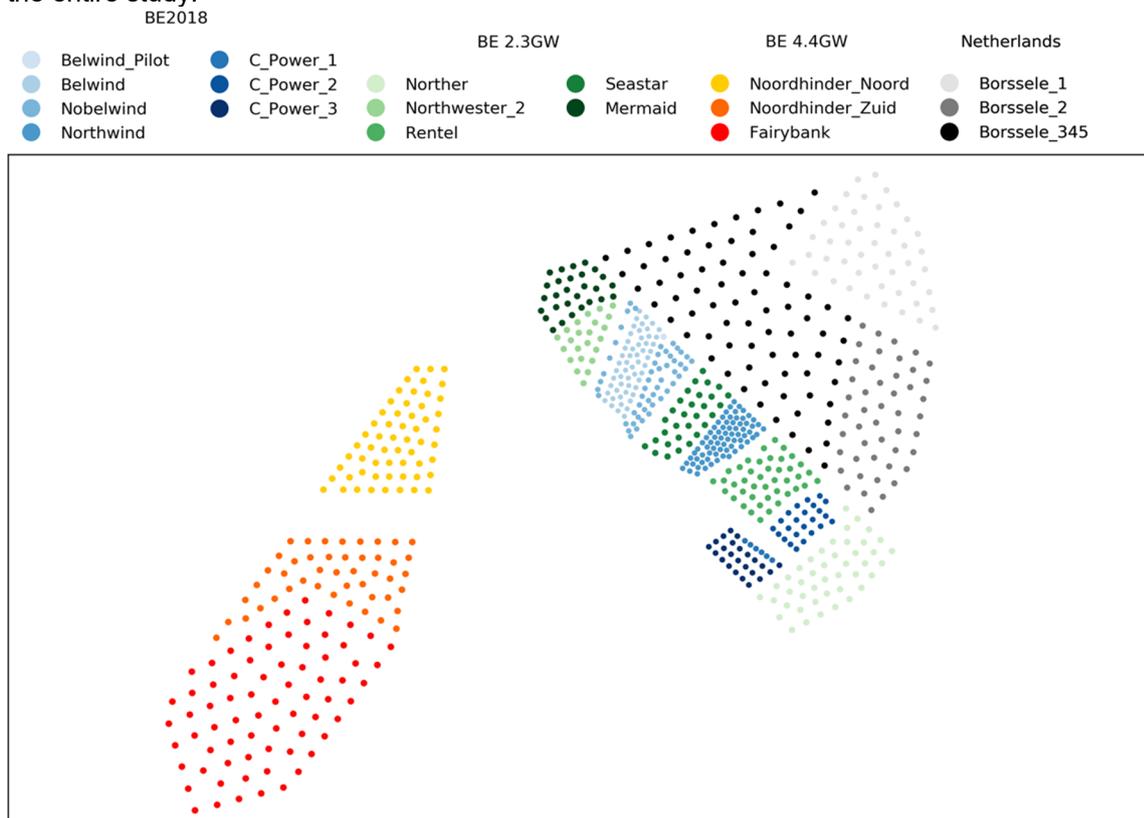


Figure 7. Plant and turbine locations for the different stages of offshore wind installations. The Dutch plants are taken into account when modelling external wake impacts on the Belgian OWPPs.

4.1 Offshore plants in model validation

The plants that belong to the BE2018 group (Belwind, Nobelwind, Northwind, C_Power_1, C_Power_2 and C_Power_3), see Figure 7, are used in the model validation. These plants are selected because they have multiple years of measurements available (see Section 6).

4.2 Extended capacities

The several stages of the installations of the Belgium offshore wind power fleet considered in the present study are shown in Figure 7. The BE 2.3GW stage consists of the full MOG I fleet (this includes the plants in BE2018 as well as Norther, Northwester 2, Rentel, Seastar and Mermaid).

The BE 4.4GW scenario consists of the estimated locations of the future MOG II plants: this scenario includes the plants in the BE 2.3GW as well as Noordhinder Noord (~700 MW), Noordhinder Zuid (~550 MW) and Fairybank (~850 MW). Two additional installation scenarios

are modelled. In BE 3.0 GW, only Noordhinder Noord is considered in addition to the 2.3 GW. In BE 4.0 GW, all of the OWPPs belonging to 4.4 GW are considered; however, they are all considered to have lower installed capacities.

The Borssele offshore cluster in the Netherlands is considered because large wake effects are expected due to its proximity to the Belgian fleet. On the contrary, the planned offshore plants in Dunkirk France are not modelled because their larger distance to the Belgian fleet makes them irrelevant in terms of farm to farm wake losses.

4.3 The scenarios

For the installation scenarios described in the previous section, different turbine technologies are modelled. The technologies are as presented in Chapter 2. The resulting scenarios, considering the different amounts of installations and different technologies, are listed in Table 4. Going from BE2018, which is used for model validation, the installed capacity increases towards 4.4 GW. All of the scenarios with 3.0 GW or more installed have the same 2.3 GW as the existing installations with fixed technology; then, different amounts of additional installations with different technologies are added to the 2.3 GW to reach the total installed capacity of the scenario.

Table 4. The studied scenarios.

Name	Installed capacity (MW)	Tech type	Storm shutdown type
BE 2018	877	Known existing data	Known existing data
BE 2.3 GW	2300 (approximately)	Known data	Known data
BE 3.0 GW	2300 + 700 additional	Tech A	25 m/s
			Moderate
			Deep
		Tech B	25 m/s
			Moderate
			Deep
BE 4.0 GW	2300 + 1700 additional (Noordhinder Noord, Noordhinder Zuid and Fairybank; all with lower installed capacity)	Tech A	25 m/s
			Moderate
			Deep
		Tech B	25 m/s
			Moderate
			Deep
BE 4.4 GW	2300 + 2100 additional (Noordhinder Noord, Noordhinder Zuid and Fairybank)	Tech A	25 m/s
			Moderate
			Deep
		Tech B	25 m/s
			Moderate
			Deep
		Tech A/B	25 m/s
			Moderate
			Deep

Notes related to Table 4:

- For BE 3.0 GW, BE 4.0 GW and BE 4.4 GW, the tech type and storm shutdown type are for the additional installed capacity; the 2300 MW part has technology specified based on known existing and planned OWPPs.
- The Tech A/B type for BE 4.4 GW has a mixture of Tech A and Tech B installations: Noordhinder Noord (~700 MW) has Tech A and Noordhinder Zuid (~550 MW) and Fairybank (~850 MW) have Tech B.

5. Methodology

This chapter presents the modelling methodology used in the MOG II analyses. This includes the CorWind tool for simulating the time series and wake modelling for including wake impacts in the CorWind simulations. Modelling of plant-behaviour during storms is also presented, and Section 5.4 explains how a filtering process is used on measured data from 2018-2019 to provide representative time series for the future scenarios based on measured time series.

5.1 CorWind

CorWind is DTU Wind Energy's tool for simulation of wind power times with realistic spatial and temporal correlations. It is the wind simulation part of the CorRES tool, which includes also solar generation simulation capabilities [2]. CorWind uses a database of mesoscale weather time series in hourly resolution over all Europe as input, and therefore it can capture the spatiotemporal variability for large scale simulations. DTU's database includes 37 years of meteorological data (1982-2018) produced using the Weather Research and Forecasting (WRF) mesoscale numerical weather prediction model [3]: WRF uses the ERA-Interim weather reanalysis datasets produced by the European Centre for Medium-Range Weather Forecasts as boundary conditions and simulates the weather over Europe with resolutions of 10 km. The downscaling from the coarser ERA-Interim data to the 10 km x 10 km resolution grid is carried out using the downscaling methods presented in [4], [5]. More information on the WRF model setup for reaching the final mesoscale data can be found in [6].

Compared to most other tools for large-scale wind power simulations, CorWind includes intra-hour fluctuations which are not captured correctly by mesoscale models even with high spatial and temporal resolutions and also the turbulent fluctuations within 10 minutes resolutions [7], [8], [9]. Information on why the mesoscale modelling systems (such as WRF) cannot capture all variability in wind can be found in [10]. The missing fluctuations are added to the mesoscale WRF data using stochastic simulation [11].

The combination of mesoscale WRF data and stochastic simulation allows two types of simulations: (1) large scale regions on continental domains with several wind power plants in resolutions of up to 5 minutes over 37 years; (2) detailed plant simulations that model each individual turbine; these simulations are required to understand the impact of storm protection technologies, which are usually specified on turbine-level rather than plant-level.

Due to the limitations of CorWind, it is currently not possible to run the simulations in 1min resolutions for the full Belgium offshore fleet over the 37 years. A resolution of 5min has been selected as it provides a compromise between the computational time and the limited added information of the within-10-minute fleet power fluctuation in both simulations and in the measured data in 1min resolution. For each simulation a reduced 15 min resolution dataset is produced by taking the mean of each variable in 5 minute resolution (or 1min resolution for the measured datasets) within each 15 minutes period. The 15min resolution data are calculated from the 5min data by taking the mean over the 15min and by shifting the resulting timeseries by 7.5min to ensure that there is no lag between the 15min and 5 min resolution timeseries.

5.2 Wake Modelling

As turbines and plants in the Belgium offshore fleet are often tightly spaced, significant wake effects are expected. Wake effects are modelled using the engineering wake model proposed by Bastankhah and Porté-Agel [12]. The wake model consists in Gaussian wind speed deficits, linear wake expansion and squared sum wake deficit superposition. This model is used because of its simplicity and because it has been formulated to hold mass and momentum conservation equations in the wake flow behind a turbine, while other engineering wake models like Jensen/Park do not. DTU's PyWake implementation of the wake model used in this study is available as open source code in <https://topfarm.pages.windenergy.dtu.dk/PyWake/>.

The wake model is used to generate a plant power curve by simulating the power outcome of the plant as function of the mean wind speed and mean wind direction over the whole plant. The plant power curve includes the wakes produced by other plants nearby, by modelling all the turbines within 40 km distance from each turbine within the plant. The resolution of the wake modelling has been chosen to be 1 degree in wind direction and 0.5 m/s in wind speeds. Finally, CorWind uses the plant power curve to interpolate the power produced by each plant on each time stamp.

An example of the wake modelling approach is shown in Figure 8 for an example OWPP in the BE2018 scenario. It can be seen that the internal wake losses are one order of magnitude larger than external wake losses. Both effects are captured in the plant power curve.

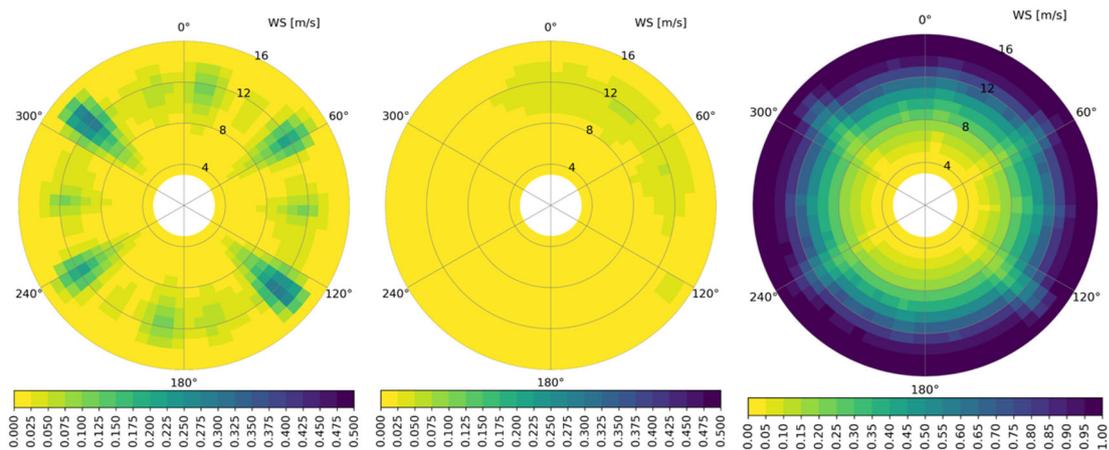


Figure 8. Example of wake modelling results for an OWPP: Left: internal wake losses; centre: external wake losses due to nearby plants; and right: plant power curve.

5.3 Storm shutdown behaviour

When simulating multiple years of generation time series with CorWind on 5 min resolution for multiple OWPPs, the simulations need to be done on plant-level; simulation of individual turbines is not feasible for such long time series. However, as the storm shutdown behaviours are given on turbine-level (Figure 2), the behaviours of the different shutdown technologies need to be modelled on plant-level. This section describes how the turbine-level shutdown information are transferred to plant-level models.

5.3.1 Turbine-level storm shutdown model

Individual turbine shutdown can be modelled in simulations with up to 1 s resolution in CorWind (while the mesoscale data are hourly, CorWind creates up to 1 s time series using stochastic

simulation, as described in Section 5.1). These simulations are used to study how a specific turbine high wind speed technology translates into the plant level shutdown/restart behaviour. In these simulations, each turbine in a plant is modelled. Because of the high temporal resolution and turbine-level resolution of these simulations, only specific events (one or a few days) are simulated. A selection of high wind speed events has been taken from the 37 years of meteorological data to represent multiple high wind cases.

In addition to the shutdown operation, the turbine-level model considers the restart operation. An example is shown Figure 9. The continuous line is effective until the turbine is shut down due to too high wind speed (the wind speeds in the figure are 10 min averages). After the shutdown, the wind speed has to get lower than the restart limit before the turbine starts to produce again. This effect is called hysteresis: it causes a time lag between the shutdown and restart operation, as it takes some time before wind speed gets lower than the restart limit after a storm event.

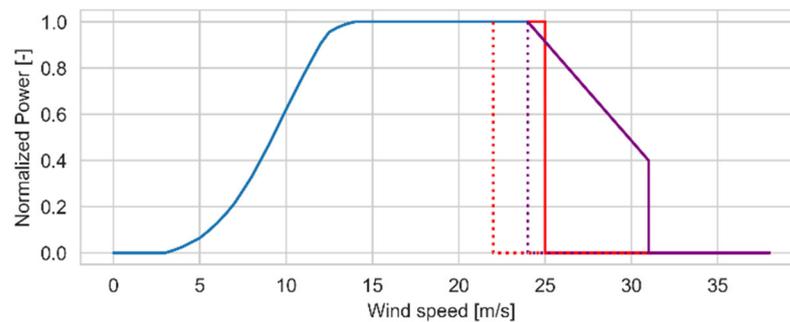


Figure 9. Storm shutdown and restart operations for the HWS Deep (magenta) and 25 m/s cut off (red) types. The dashed lines show the restart limits.

5.3.2 Resulting plant-level storm shutdown behaviours

The resulting plant-level storm shutdown behaviours for the three different shutdown types are shown in Figure 10. The blue dots show results from the 1 s resolution turbine-level runs; the red lines show the plant-level model based on the turbine-level simulations (the dashed line shows the plant-level power curve without the shutdown procedure: this line shows the power curve considering the controlled reduction of generation at high wind speeds, but without the shutdown action that takes the generation all the way to zero).

In Figure 10, it can be seen that the plant-level curve is smoother around the change from rated power to the part where generation is reduced compared to the turbine-level curve. Also, the cut-off does not happen as immediate on the plant-level: even for the 25 direct cut-off type, the plant does not completely shut down when the plant-level 10 min wind speed gets higher than 25 m/s. This is because it is unlikely that all the turbines of the plant reach a wind speed higher than 25 m/s exactly at the same time.

Plant-level hysteresis modelling is part of the model shown in Figure 10 with red lines. This means that if wind speed decreases after reaching a wind speed value over the shutdown limit, the plant will remain partly in shutdown before the wind speed gets lower than the restart limit. This models the phenomena where some of the turbines of the plant are in shutdown, whereas others still generate.

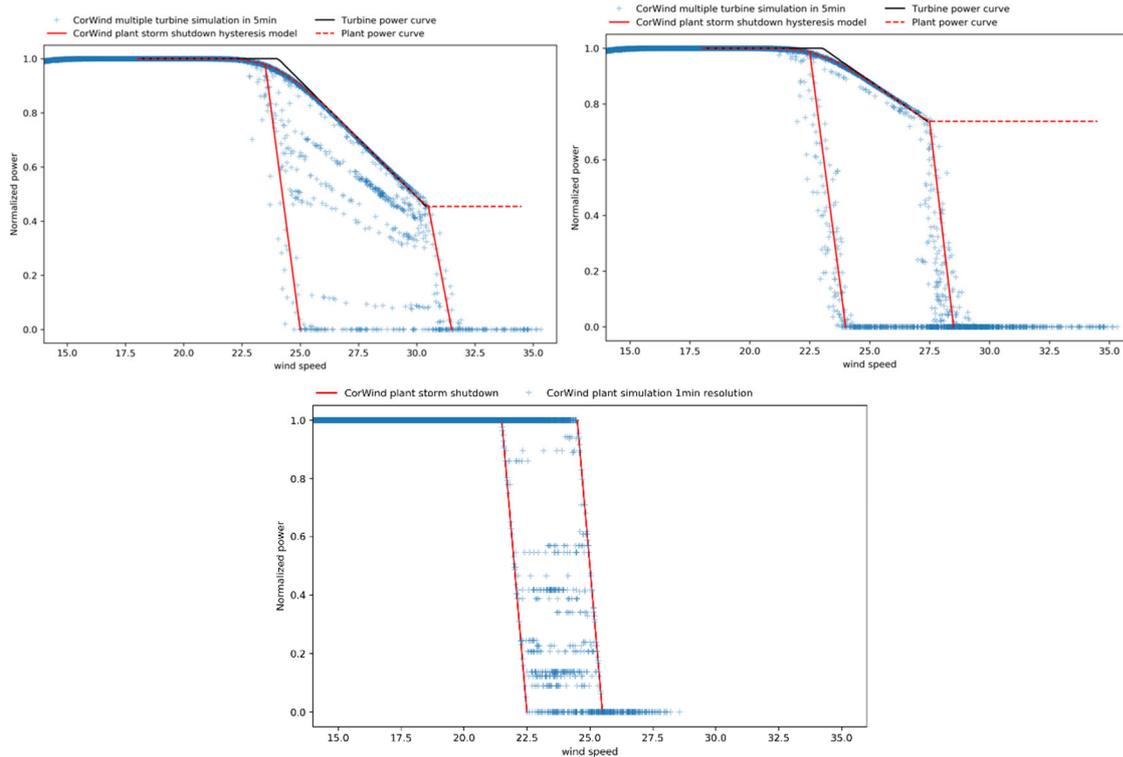


Figure 10. Calibration of storm-shutdown models in CorWind based on aggregated individual turbine simulations for different high wind speed storm operation technologies: top left: Deep; top right: Moderate; and bottom: 25 direct cut-off

5.4 Filtering measured data to represent a future scenario

Results presented in this report are based on simulated data from CorWind. These simulations relate to meteorological data from 1982 to 2018. However, the meteorological data cannot be taken to represent the reality exactly on 5 min or even hourly resolution (see Section 5.1): even though the high and low wind events happen approximately at the same times in the meteorological data and in reality (measured data), e.g., the exact time when a storm event affects an OWPP in the simulation is not the same as in reality. In addition, the stochastic simulations in CorWind, which add the missing variability to the data to better represent the ramp rates, do not add ramps at the same times as in measured data. For these reasons, the results from CorWind are assessed statistically; e.g., how many days in a year on average a significant ramp event is expected to occur.

However, in order to evaluate the impact of the additional capacity on the assessment of the flexibility needs and dimensioning of balancing reserves, Elia needs to combine offshore wind time series representing a future scenario to measured data from other sources (e.g., onshore wind and solar generation, load). Due to the reasons explained above, the simulated data cannot be combined to measured data as it may cause correlations between the different sources to be incorrectly represented. Thus, DTU has created a process where measured historical offshore wind generation data can be filtered to represent a future scenario with more OWPPs installed. The following sections explain how this process works for actual and forecasted generation.

5.4.1 Transformation and filter for actual generation

The starting point for applying the filter on 2018 and 2019 data are the measured 1 minute resolution generation data provided by Elia for each OWPP. However, as it was noticed that the 1 minute data includes control actions, they were first removed. Control actions cause variability in the data which are not caused by weather variability; an example can be seen in Figure 11, where an OWPP drops down for a significant time period (wind speeds are not high, so this is not caused by storm shutdown), causing an extreme 1 min up- and down-ramp.

The data processing consists on removing the individual plant production (at the moment it occurs and during the following 15 min) when both of the following conditions are met:

- 1 min power fluctuation is above 0.1 of the total installed capacity
- Fleet wind speed is lower than 18 m/s

The resulting distribution of 1 min fleet (BE 2018 installations) power fluctuations is shown in Figure 12. Note that the removal of the events has a marginal impact on the statistics of the 1 min power fluctuations in terms of mean, standard deviation (std), 1% quantile and 99% quantile. The main impact can be seen in the minimum (min) and maximum (max), as expected.

After the control actions have been removed, the measured data from the individual OWPPs that belong to BE 2018 (see Section 4.1) are aggregated and taken to 5 min resolution. This time series is then used as the starting point for the filtering process.

First, the 5 min resolution time series is transformed to a time series that represents the statistics of an extended capacity scenario, e.g., the 4.4 GW scenario with Tech B. The transformation considers the probability distribution function (PDF) of the time series; it applies the increase in capacity factor, as shown in Chapter 7, to the time series. The transformation considers also other statistics, such as standard deviation (SD) and percentiles, as the entire PDF is transformed. This is done using probability integral transformations based on the CorWind simulations of the BE 2018 and the extended capacity scenarios. Figure 13 shows the transformation procedure: first on the simulated data, and then as applied on the measured data (bottom subplot).

A filter has been designed to consider also the temporal dependency structure. This is required to capture the impact of geographical smoothing on reducing the standardized generation ramp rates, as shown in Chapter 8. The filter is a linear combination of three Gaussian moving average operators calibrated to match the autocorrelation of the extended capacity time series without producing lag in the output. An example of the autocorrelations before and after the filter can be seen in Figure 14: when applying both the transformation and the filter on the BE 2018 data, the resulting time series shows the same temporal correlation structure as the BE 4.4 GW Tech B data.

The results of applying the probability integral transformations and geographical smoothing filter on the 5 min measured BE 2018 aggregate generation can be seen in Figure 15. The reduction in 5 min ramp SD is similar to the CorWind simulation results on 37 years (see Section 8.1).

The filtering process is not valid for storm shutdown events. The high wind speed events (fleet-level wind speed > 22 m/s) are thus identified and filtered time series values are not given for those high wind speed events.

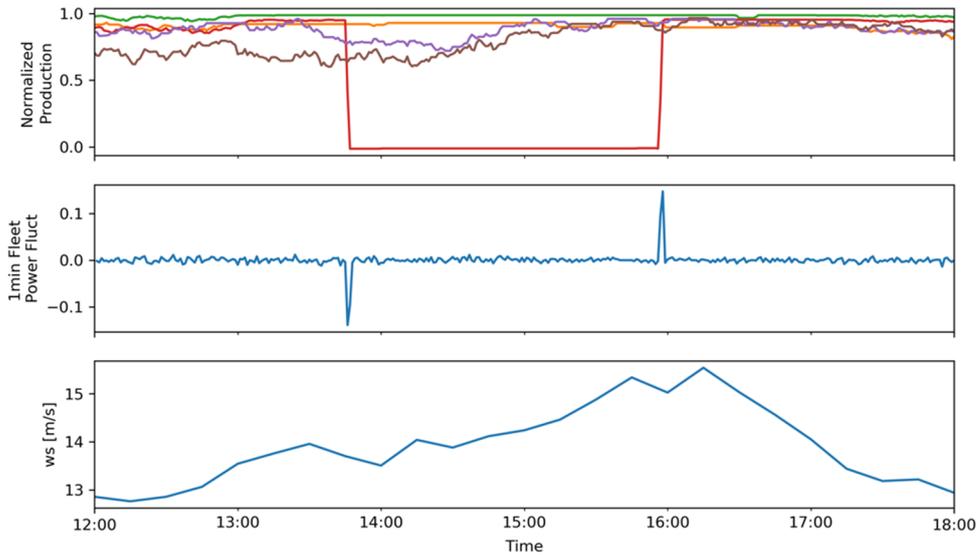


Figure 11. Extreme 1 min power fluctuation event on 2018-08-19; the top subplot shows generation from individual OWPPs; other subplots show fleet-level values.

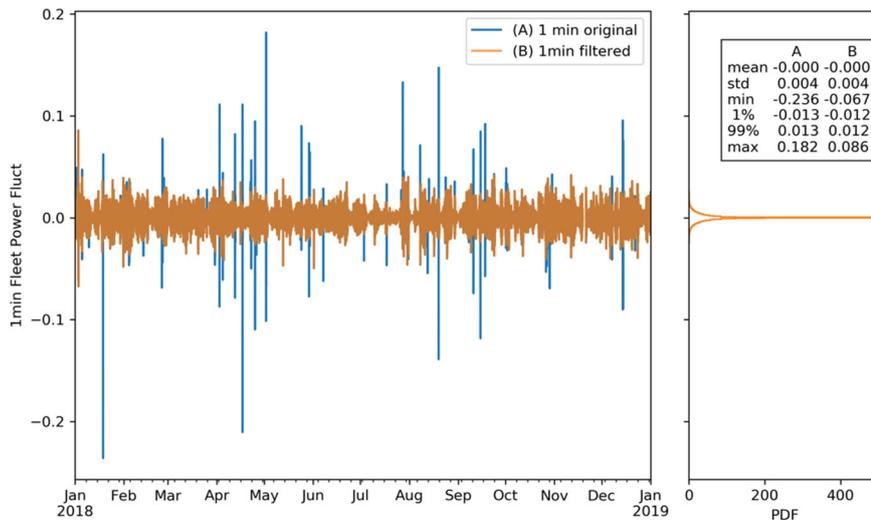


Figure 12. Measured 1 min fluctuations of the normalized fleet power: A: original dataset; B: after the removal of the control actions.

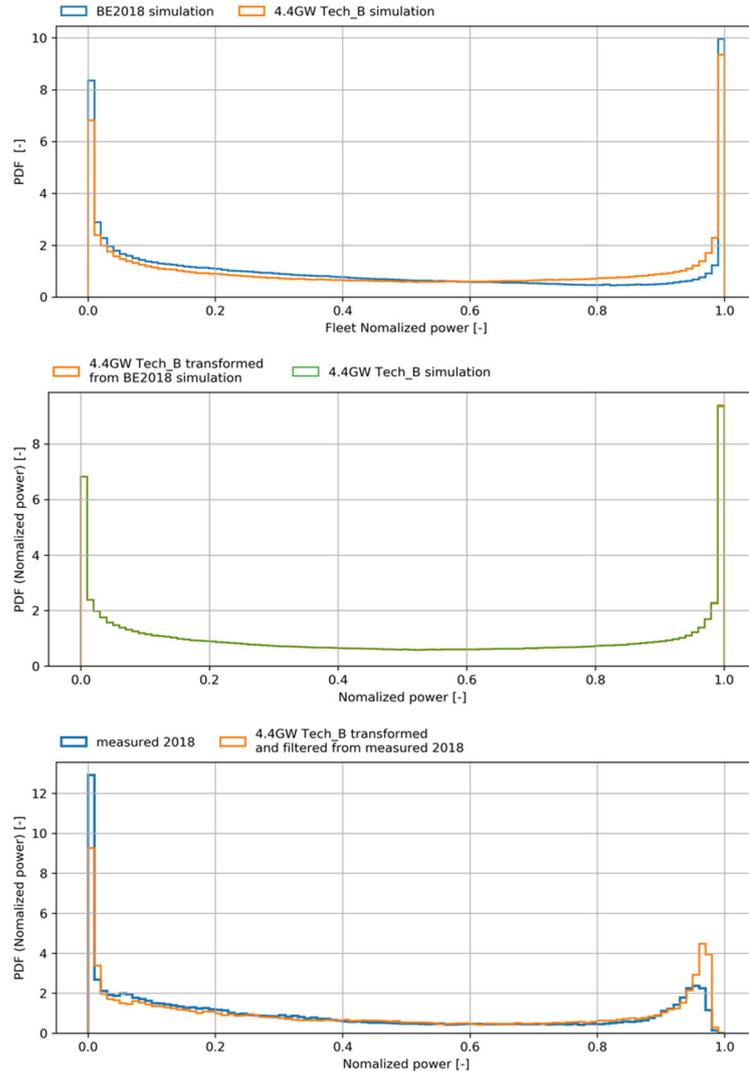


Figure 13. Result of the probability integral transformation for the 4.4 GW case with Tech B. Top: CorWind simulations for BE 2018 and BE 4.4 GW Tech B; middle: simulated BE 2018 transformed to BE 4.4 GW Tech B vs. the simulated BE 4.4 GW Tech B; bottom: measured 2018 and measured 2018 transformed to represent the BE 4.4 GW Tech B scenario.

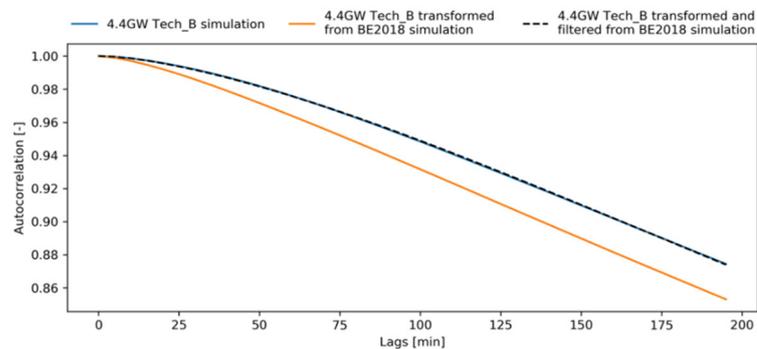


Figure 14. Autocorrelation of the resulting filtered time series for BE 4.4 GW Tech B. The orange line shows the result when only the PDF transformation is applied; the dashed line shows the result when also the filter considering temporal correlations has been applied.

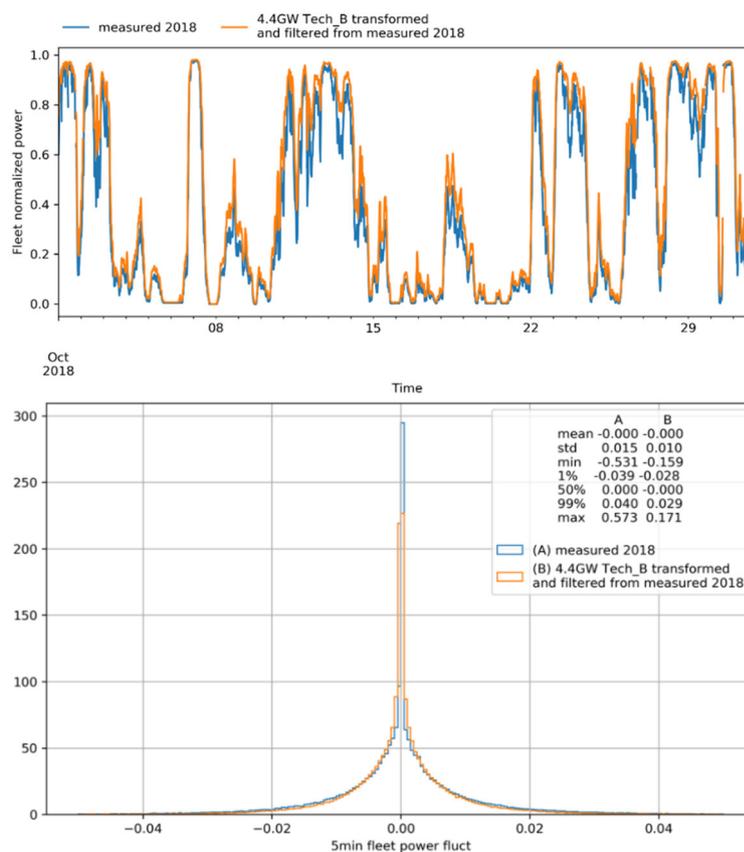


Figure 15. Example of the measured BE 2018 time series and the resulting filtered time series representing the 4.4 GW case with Tech B on the top, and comparison of 5 min power fluctuations in the bottom.

5.4.2 Representing forecast error changes

The forecasts measured from 2018 and 2019 are also processed to represent the expected reduction in fleet-level forecast errors shown in Chapter 10. This is achieved by using the reported reductions in forecast error SDs from BE2018 to the different simulated extended capacity scenarios. The forecast errors are first calculated for day-ahead, intraday and “Last” forecasts for the measured aggregated BE 2018 time series. Then these forecast errors are scaled down using the SD reduction factors from Chapter 10. The resulting filtered forecast errors are then combined to the filtered generation for the extended capacity scenario (transformed and filtered as described in the previous section) to find the forecast for the analysed scenarios.

6. Model validation

This chapter presents the measured data from Elia used in CorWind model validation in Section 6.1. Section 6.2 presents validation results on plant level and Section 6.3 on the aggregate offshore wind generation of Belgium. Validation considers statistics, such as capacity factors (CFs) and standard deviations (SDs), and probability density functions (PDFs). Ramp rates and behaviour during storms are also validated Section 6.4 looks also at the simulation of forecasts, and resulting forecast errors. Section 6.5 gives conclusions on the model validation.

6.1 Wind generation and wind speed measurements

6.1.1 Wind generation data

The measured generation data from the following OWPPs on 15 min resolution are used for model validation: Nobelwind, Belwind, Northwind, C_Power_1, C_Power_2 and C_power_3. The 15 min resolution data from 2015 to 2018 are used as the main validation dataset. Wind generation data is available also on 1 min resolution for 2018; these data are aggregated to 5 min resolution in model validation to assess CorWind's capability of modelling 5 min ramps. Some OWPPs do not have measurements covering the entire time range from 2015 and 2018; as much data as possible are used in model validation in plant level and aggregate level. Day-ahead, intraday and the latest ("Last") forecast errors are also available on 15 min resolution for each OWPP. The day-ahead, intraday and Last forecast horizons are aligned with Elia's forecast horizons and timing.

2019 data are not used in model validation due to reasons explained in Section 6.1.3.

6.1.2 Wind speed data

Wind speed data are available from Nobelwind, Belwind and Northwind and from C_Power. For C_power, it is not clear to which C_Power (1, 2 or 3) the wind speed data relates to; as the C_Power OWPPs are close by, the same wind speed data are used to represent wind speeds in each of the C_Power OWPPs. Wind speed data are available from 4 turbines per OWPP, from the 4 corners of each plant. For comparison to CorWind simulations, which are carried out per plant, mean of the 4 turbines is taken to represent the effective wind speed of the plant. Wind speeds and 10 min wind speed ramps are visualized for an example OWPP in Figure 16. The ramps show a non-Gaussian shape, with significant number of large down- and up-ramps. The same behavior was seen for all measured locations; for another example, wind speed ramps are shown in Figure 17. The distributional information on wind speeds was used in CorWind calibration, as similar behavior was seen in measured wind speeds from all OWPPs with data.

For the wind speed range where wakes have an impact (approx. below 14 m/s), the measured data is expected to include wake impacts. As wind speeds from CorWind simulations are given without wake impact (with wakes considered in the transformation from wind speed to generation), this difference is taken into account when comparing measured and simulated wind speeds. Generation data can be compared directly between the measurements and simulations. Figure 18 shows an example where the 15 min generation data and 10 min wind speed data (with linear interpolation) has been combined. When comparing to simulations, the values with wind speed between 5 and 15 m/s and generation 0 are not considered; this was done because even with storm protection considered, in this wind speed range generation should be above 0. Such data

points were considered to be either measurement errors or indicating that the whole OWPP is unavailable (CorWind does not model unavailability). The time steps were marked as not available in the measured data. This was done for all OWPPs.

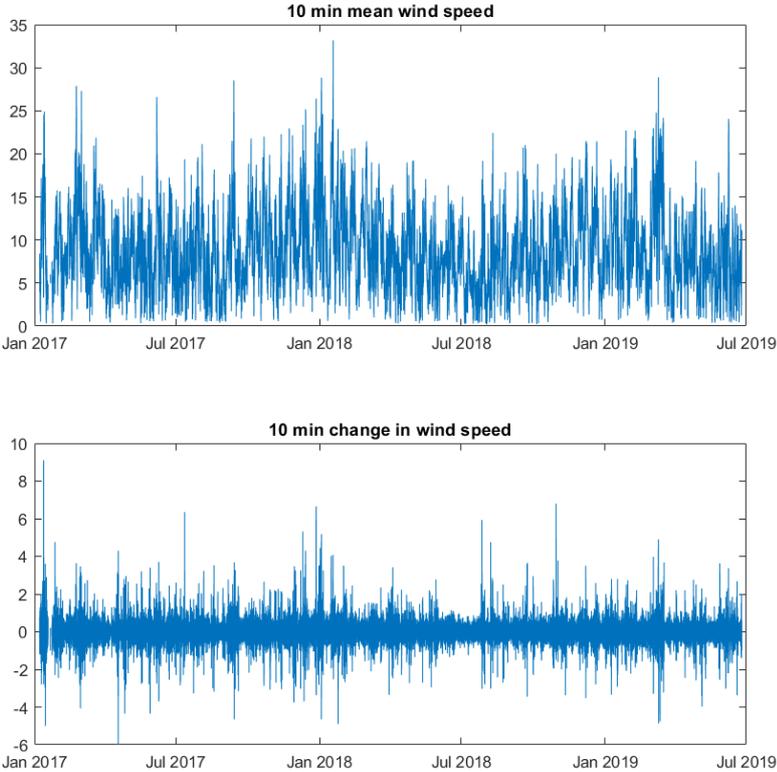


Figure 16. Measured wind speeds and 10 min wind speed ramps at an OWPP; 10 min resolution, mean of the 4 measured turbines.

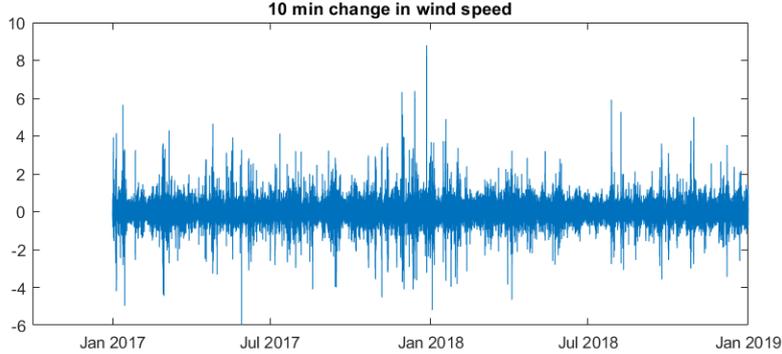


Figure 17. Measured 10 min wind speed ramps at an OWPP; 10 min resolution, mean of the 4 measured turbines.

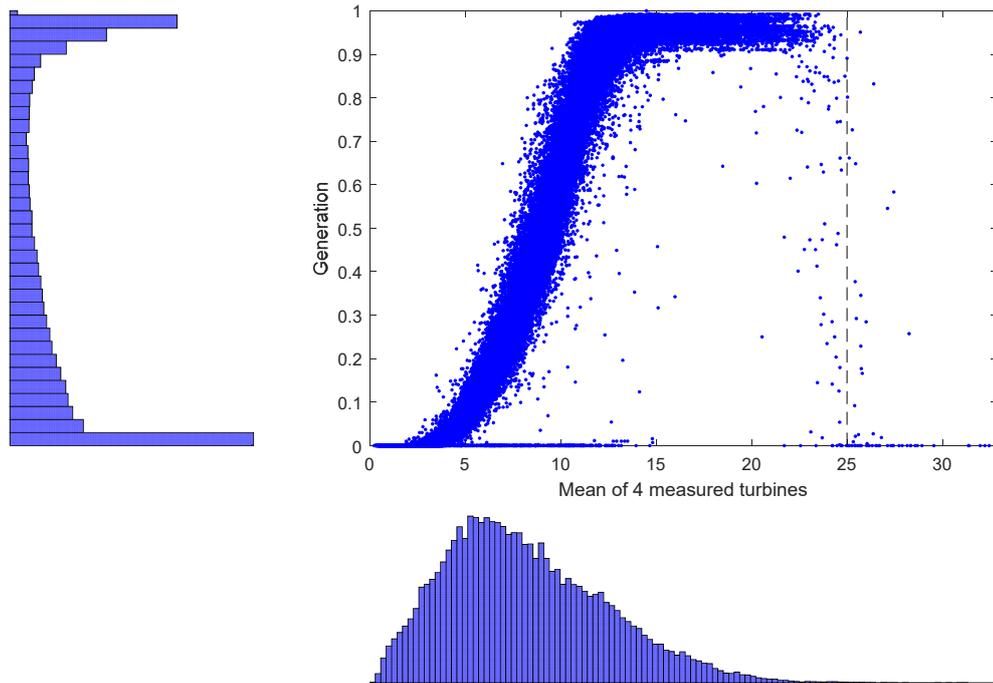


Figure 18. Wind speed (mean of the 4 measured turbines) and standardized generation scatter plot with histograms of an OWPP. Dashed line shown the turbine-level storm shutdown limit (25 m/s in this case).

6.1.3 About the time range of measurements for validation

The meteorological WRF data is available from 1982 until 2018. Thus, data after the end of 2018 cannot be simulated. As it cannot be simulated, it also cannot be compared to measured data in model validation; thus, only measurements until the end of 2018 are used when validating CorWind.

6.2 Plant level validation

6.2.1 Capacity factors

The differences in the measured and simulated capacity factors (CFs) for the six OWPPs in the validation are shown in Table 5. CorWind shows slightly higher CFs than measurements. The simulations assume 100 % availability for the OWPPs, so the tendency to get slightly higher CFs in the simulation is expected. Information about the availability of turbines in the different plants was not available.

Table 5. Differences in measured and simulated capacity factors.

	Difference
OWPP_1	-0.3%
OWPP_2	2.5%
OWPP_3	2.0%
OWPP_4	9.3%
OWPP_5	3.5%
OWPP_6	11.9%

6.2.2 Generation probability distributions

Simulated and measured generation probability density (PDF) is visualized for two example OWPPs in Figure 19 and Figure 20. The impact of assuming 100 % availability can be seen in the figures, as CorWind simulates exactly full generation when wind speed is favorable, whereas in measured data generation exactly at installed capacity is relatively rare. For both OWPPs, the peak in the PDF near 1 seems to be approximately at 0.95, suggesting on average unavailability of around 5 %. The PDFs for other OWPPs showed similar results. Standard deviations (SDs) of all the OWPPs are given in Table 6; it can be seen that simulated and measured SDs are similar.

Even though information about unavailability of turbines was not available, an option to roughly consider the unavailability in the simulations would be to multiple all simulated generation time series with a constant factor, e.g., 0.95. However, this would cause also the maximum generation to be reduced by 5 %; as can be seen in Figure 19, the measured data shows that sometimes the plant generation is at full installed capacity. Thus, the multiplication by 0.95 was not applied, and all results are given assuming 100 % availability of the plants. Post-processing of the simulated time series assuming 100 % availability can be done later, if required, to assess the impact of unavailability.

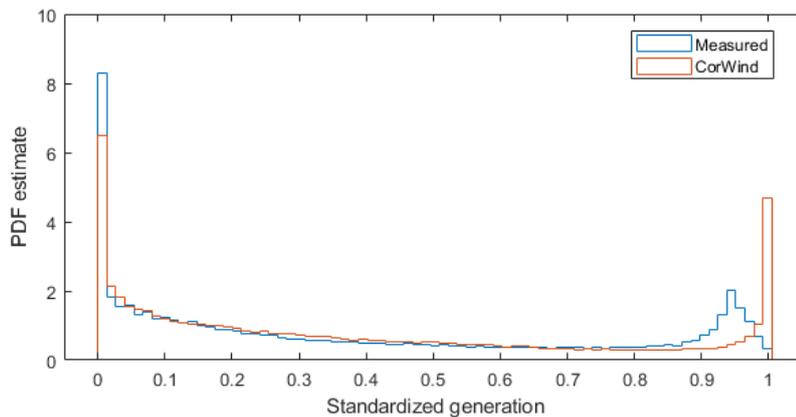


Figure 19. Generation PDF of the measured and simulated data for an example OWPP. Standardized generation is 1 when the OWPP is generating at installed capacity.

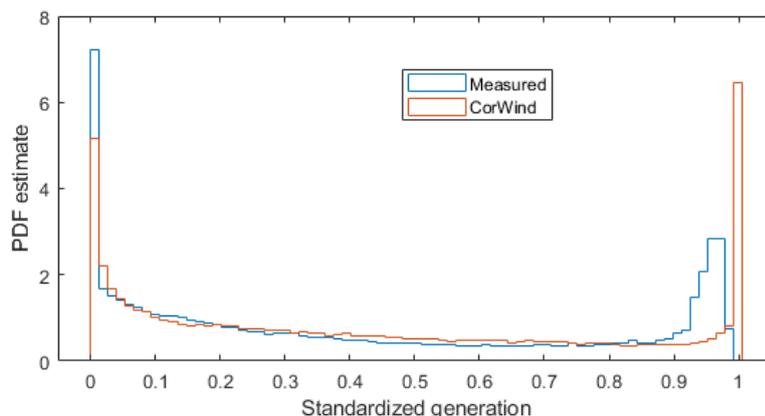


Figure 20. Generation PDF of the measured and simulated data for an example OWPP. Standardized generation is 1 when the OWPP is generating at installed capacity.

Table 6. Standard deviations of simulated and measured generation.

	Measured	CorWind	Difference
OWPP_1	0.343	0.340	-1.0%
OWPP_2	0.371	0.364	-2.1%
OWPP_3	0.357	0.349	-2.2%
OWPP_4	0.338	0.362	7.1%
OWPP_5	0.337	0.348	3.4%
OWPP_6	0.335	0.355	6.1%

6.2.3 Correlations

Correlations between generations from the OWPPs are shown Figure 21. It can be seen that generations from all OWPPs are highly correlated, with OWPPs very close by showing the highest correlation. The simulations show similar correlations compared to the measured data. These correlations are calculated as $\text{Cor}(p_{t,i}, p_{t,j})$, where $p_{t,i}$ is generation at plant i at time t . Both measured and simulated are 15 min resolution.

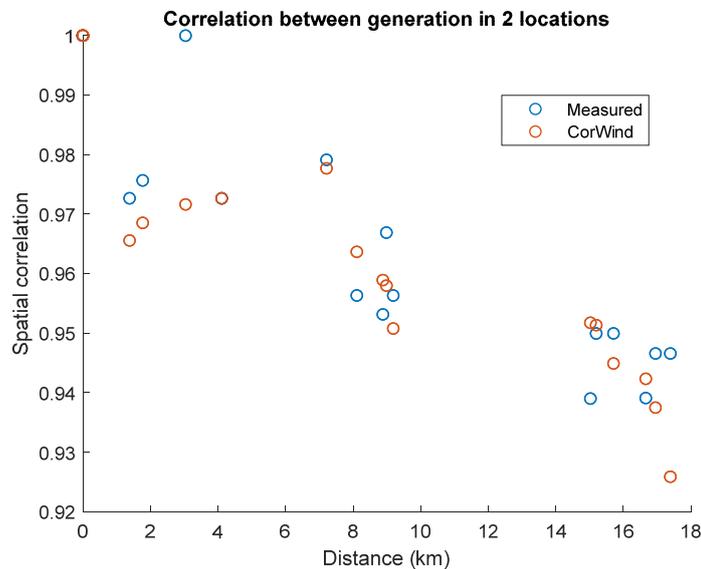


Figure 21. Correlation between generations from two OWPPs consider all combinations between the six OWPPs used in validation, plotted against the distance between the OWPPs.

6.2.4 Ramp behavior

SDs of 15 min ramp events are shown for the OWPPs in validation for the measured and simulated data in Table 7. The ramp SDs from CorWind and the measured data are similar.

Figure 22 shows how 15 min and 1 h ramps at the different OWPPs are correlated. It can be seen that the 15 min ramps have a relatively low correlation for the plants far away from each other; however, on the 1 h level, the correlation remains higher than 0.4 even for the plants around 18 km from each other. These correlation of ramps are calculated as $\text{Cor}(\Delta p_{t,i}, \Delta p_{t,j})$, where $\Delta p_{t,i}$ is ramp (change in generation) at plant i at time t during a time interval (e.g., 15 min). E.g., for 15 min ramps with 15 min resolution data, $\Delta_{15\text{min}}p_{t,i} = p_{t,i} - p_{t-1,i}$, where $p_{t,i}$ is generation at 15 min resolution. $\Delta_{15\text{min}}p_{t,i}$ is thus the difference between the mean generation values of two successive quarter hours. Hourly ramps are analysed on 15 min resolution, i.e., $\Delta_{\text{hourly}}p_{t,i} = p_{t,i} - p_{t-4,i}$.

The different dependency of ramp correlation on distance for different ramp durations (15 min, 1 h) show that geographical smoothing is expected to have different impact of different time scales. It needs to be noted that even if correlation between ramps at two locations is zero, a ramp up or down can still happen simultaneously at the locations; but is less likely than in a case where the correlation is high.

Table 7. Standard deviation of 15 min ramps for measured and simulated data.

	Measured	CorWind	Difference
OWPP_1	0.0499	0.0456	-8.7%
OWPP_2	0.0470	0.0453	-3.6%
OWPP_3	0.0506	0.0459	-9.2%
OWPP_4	0.0469	0.0538	14.6%
OWPP_5	0.0468	0.0477	2.0%
OWPP_6	0.0486	0.0469	-3.5%

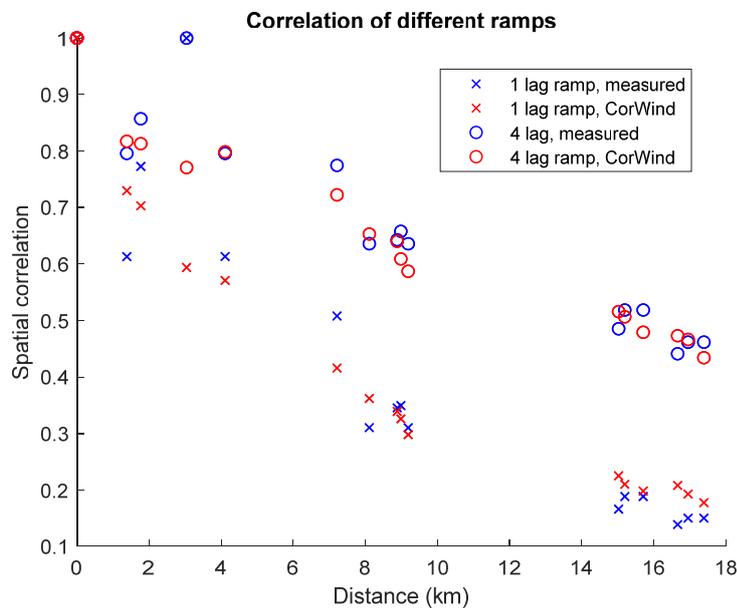


Figure 22. Correlations between 15 min (1 lag) and 1 h (4 lag) ramps for the measured and simulated data, plotted against distance between the OWPPs. 1 h ramp means difference in generation in 1 h on 15 min resolution (i.e., lag 4).

6.3 Aggregate generation validation

6.3.1 Capacity factor and generation probability distribution

CF and SD for the aggregate offshore wind generation of all the OWPPs in the validation (around 877 MW) are shown in Table 8. Both statistics are similar in the measured and simulated data. If availability would be around 95 %, the effective CF of the CorWind simulation would be 0.395, which is very close to the measured CF. Figure 23 shows that the simulated and measured PDFs are similar, expect for values between 0.85 and 1, which is expected as CorWind simulations do not consider unavailability.

Table 8. Capacity factor and standard deviation of the aggregate generation of the OWPPs in validation; all in standardized generation.

	CF	SD
Measured	0.399	0.350
CorWind	0.416	0.351

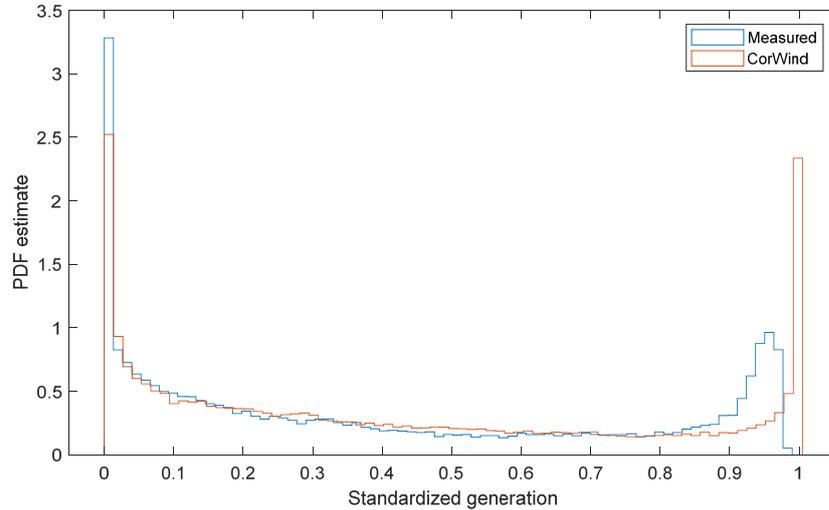


Figure 23. Generation PDF of the measured and simulated data for the aggregate of BE 2018 (the validation OWPPs).

6.3.2 Ramp behavior

The ramp behavior of aggregate offshore wind generation on 5 min resolution is shown in Figure 24 and Table 9. All statistics are similar in measured and simulated data; the minimum is lower in the simulated data compared to measurements; however, as the minimum is a single value over the entire period, and as the low percentiles are similar in measured and simulated data, this was not considered to be an issue

The ramp behavior on 15 min resolution is shown in Figure 25 and Table 10. The probability distributions of the ramps are similar for the measurements and simulations. It can be seen that the ramp SD is similar for measured and simulated data. Also the min and max ramps are similar. The most extreme percentiles (0.1 and 99.9) are somewhat closer to zero in the simulated data compared to the measurements, indicating that the simulation gives slightly lower likelihood for the most extreme ramps. However, measured data can include events which are not in simulations, such as cable faults or control actions, which can appear as ramp events. As the simulations do not include such events, it was not considered possible to assess the exact reason for the difference. The simulations are thus considered to be valid for simulating the ramp events; however, it needs to be noted that the likelihoods of the most extreme ramps may be slightly underestimated in the simulations.

Similar information is given for 1 h ramps (15 min resolution data) in Table 11 and Figure 26. The ramp SD and the minimum and maximum values are similar in simulated and measured data. The most extreme ramps are slightly underestimated in CorWind compared to the measured data.

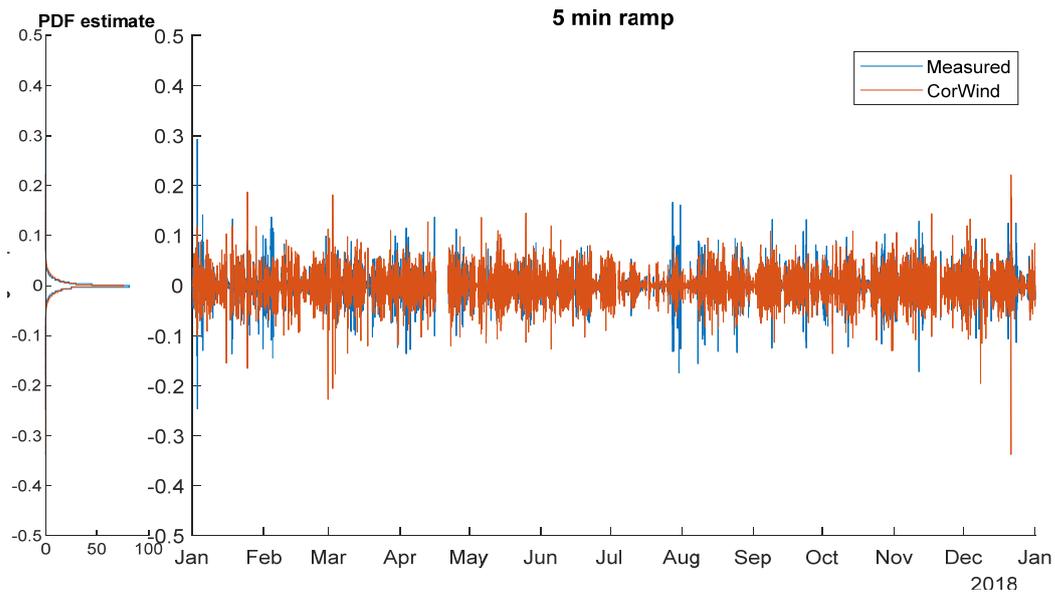


Figure 24. Time series plots of the simulated and measured 5 min ramps of the aggregate offshore wind generation, with estimated PDFs on the left.

Table 9. 5 min ramp statistics of the aggregate offshore wind generation (Prct = percentile).

	mean	SD	min	Prct 0.1	Prct 1	Prct 5	Prct 95	Prct 99	Prct 99.9	max
Measured	0.000	0.013	-0.247	-0.089	-0.040	-0.020	0.020	0.040	0.081	0.292
CorWind	0.000	0.015	-0.338	-0.078	-0.043	-0.024	0.025	0.044	0.076	0.221

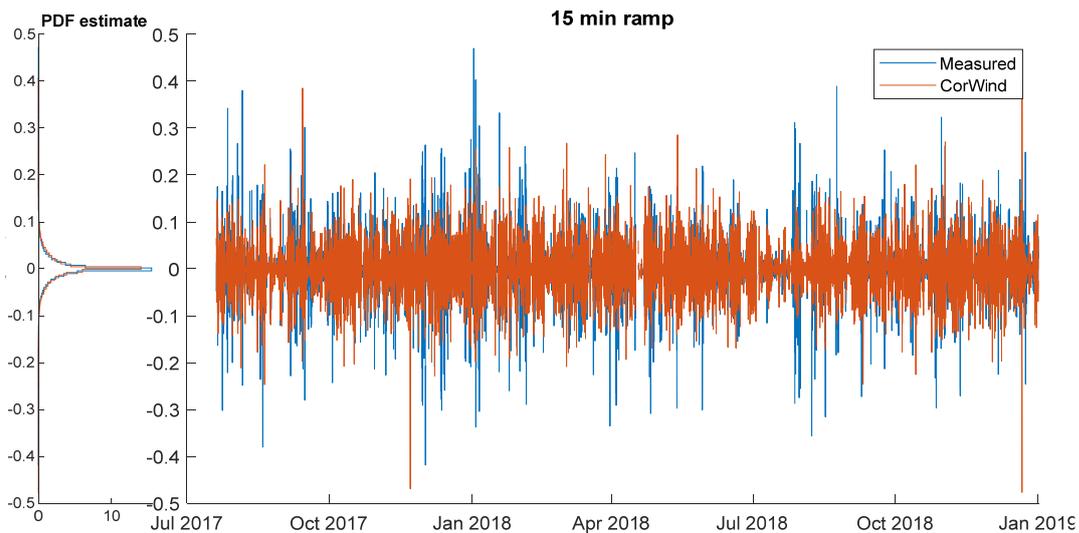


Figure 25. Time series plots of the simulated and measured 15 min ramps of the aggregate offshore wind generation, with estimated PDFs on the left.

Table 10. 15 min ramp statistics of the aggregate offshore wind generation (Prct = percentile)

	mean	SD	min	Prct 0.1	Prct 1	Prct 5	Prct 95	Prct 99	Prct 99.9	max
Measured	0.000	0.033	-0.419	-0.226	-0.099	-0.048	0.049	0.101	0.205	0.470
CorWind	0.000	0.032	-0.477	-0.151	-0.091	-0.051	0.052	0.091	0.156	0.405

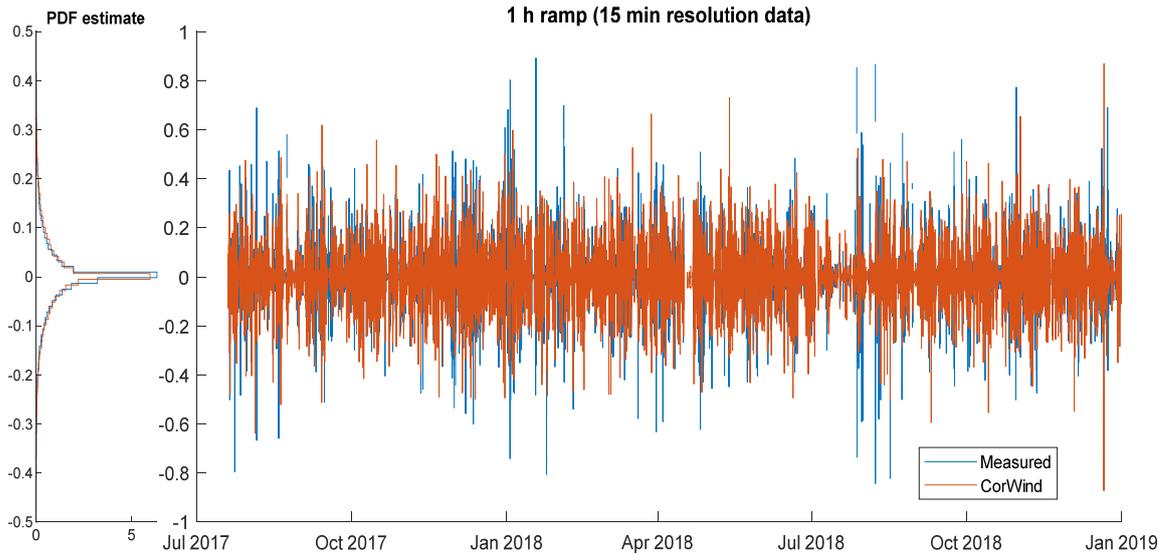


Figure 26. Time series plots of the simulated and measured 1h ramps of the aggregate offshore wind generation, with estimated PDFs on the left.

Table 11. 1 h ramp statistics of the aggregate offshore wind generation (Prct = percentile).

	mean	SD	min	Prct 0.1	Prct 1	Prct 5	Prct 95	Prct 99	Prct 99.9	max
Measured	0.000	0.087	-0.843	-0.495	-0.255	-0.131	0.135	0.270	0.511	0.892
CorWind	0.000	0.089	-0.872	-0.432	-0.249	-0.143	0.148	0.257	0.429	0.870

6.3.3 Storm shutdown likelihoods

Scatter plots of the aggregate wind speeds and generations are shown in Figure 27. It can be seen that both the measured and simulated data reach points where the aggregate wind speed affecting the region is very high and the generation is low due to many, or even all, plants being in storm shutdown. The wind speed distributions of measured and simulated data seem different for wind speeds below 15 m/s; however, this is expected due to measurements including the wake effect and CorWind showing wind speeds without wake effects (in CorWind, wakes are considered when transforming wind speeds to generation, as explained in section 5.2). Considering the generation distribution, it needs to be noted that CorWind simulations assume 100 % availability.

The likelihoods of very high wind speed events are shown in Table 12 for the measured and simulated data. The likelihoods are similar; however, CorWind shows slightly less data points above 28 m/s. This may (at least partly) explain the slight underestimation of the extreme events described in Section 6.3.2. See Section 6.3.4 on how the very highest wind speeds are modelled in CorWind.

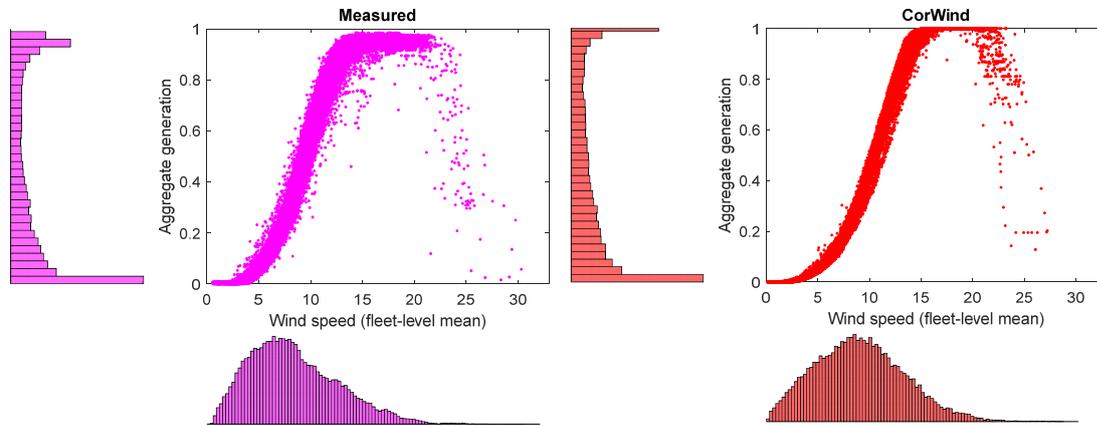


Figure 27. Scatter plots of fleet-level wind speeds (averages weighted by installed OWPP capacities) and aggregate generation of the studied OWPPs.

Table 12. Likelihoods of high wind speed events.

Fleet-level mean wind speed above (m/s)	Measured (%)	CorWind (%)
18	2.312	2.642
20	0.815	0.900
22	0.292	0.303
24	0.125	0.082
26	0.023	0.028
28	0.009	0.004
30	0.001	0.000

Data from 2017-2018, when all plants have recordings (only simulations of those time steps where measurements are available are considered).

6.3.4 Modelling the probabilities of very high wind speeds

Based on the measured wind speeds from the Belgian OWPPs, the very highest wind speeds from the mesoscale WRF model are scaled up by 8 %, as shown in Figure 28. This is done to better match the probabilities of very high wind speeds seen in the measured data. The high wind speed percentiles and maximum 10 min wind speeds for the OWPPs in the validation are shown in Table 13 for the measured data, WRF directly and CorWind simulation. It can be seen that WRF shows lower high percentiles and maximums compared to the measured data; the CorWind simulation (with the 8 % scale up) shows on average similar percentiles and maximums compared to the measurements; individual OWPPs show some differences compared to CorWind (results for individual OWPPs are reported to Elia, but are not shown in this report). Note that the maximums in CorWind are not directly 8 % higher than the maximums in WRF, because CorWind

includes also the stochastic fluctuation simulations that are added to the mesoscale WRF data (see section 5.1).

The need to scale up the highest WRF wind speeds to represent the actual maximum wind speeds is noted in literature [13], and it was thus considered justifiable in the modelling. The results in Table 12 and Table 13 show that the resulting CorWind simulations represent well the likelihoods of very high wind speeds compared to measured data (Table 12 includes the 8 % increase of the highest mesoscale wind speed).

Table 13. Very high wind speed statistics for the OWPPs with wind speed measurements.

	Percentile 99.9			Percentile 99.99			Max		
	Measured	WRF directly	CorWind	Measured	WRF directly	CorWind	Measured	WRF directly	CorWind
Mean of individual OWPPs	25.2	22.8	23.9	28.2	25.4	27.9	31.3	26.2	30.0

The statistics are based on 10 min mean wind speeds. Data from 2015-2018, per OWPP as much data used as measurements are available (only simulations of those time steps where measurements are available are considered). For the measured data, the mean values of the 4 measured turbines per OWPP were used (to represent plant-level wind speeds). The CorWind runs include the 8 % hi-wind scale up.

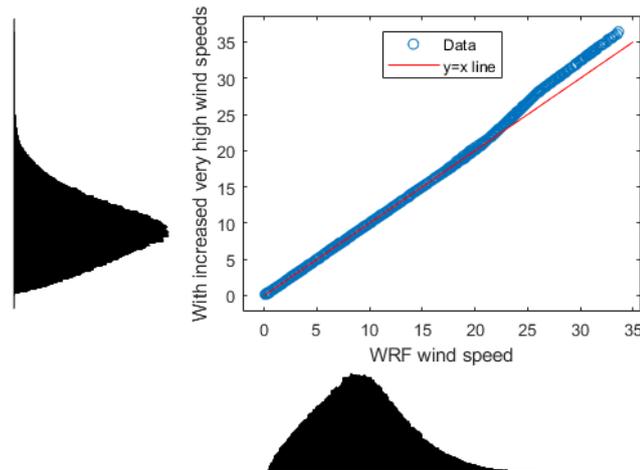


Figure 28. Increase of the highest mesoscale WRF wind speeds for an example location. Wind speeds over 26 m/s are increased by 8 %, with linear increase starting at 20 m/s. The plot includes the entire 37 years of data.

6.4 Forecast errors

6.4.1 Day-ahead forecasts

PDF and statistics of the measured and simulated day-ahead forecast errors are shown in Table 14 and Figure 29. Although aggregate statistics are shown, each OWPP is simulated in CorWind. The forecast SD is slightly lower in measured data compared to CorWind; however, the percentiles and the min and max forecast errors are similar.

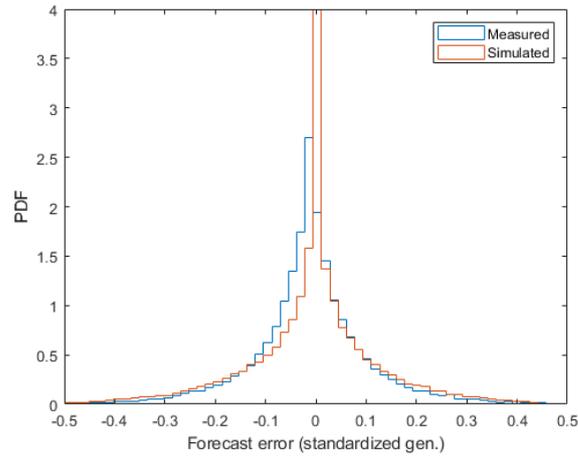


Figure 29. Measured and simulated day-ahead forecast error PDFs; aggregate of all the OWPPs belonging to validation (BE 2018). Data from 2017-2018, when all plants have recordings (only simulations of those time steps where all measurements are available are considered).

Table 14. Day-ahead forecast error statics for the aggregate of the validation OWPPs (BE 2018).

	mean	SD	min	Prct 0.1	Prct 1	Prct 5	Prct 95	Prct 99	Prct 99.9	max
Measured	-0.010	0.118	-0.824	-0.547	-0.349	-0.204	0.183	0.326	0.526	0.815
CorWind	-0.007	0.135	-0.870	-0.595	-0.403	-0.245	0.218	0.359	0.522	0.809

Data from 2017-2018, when all plants have recordings (only simulations of those time steps where all measurements are available are considered).

6.4.2 Intraday forecasts

PDF and statistics of the measured and simulated intraday forecast errors are shown in Figure 30 and Table 15. As with the day-ahead forecast, CorWind shows slightly higher SD; however, the percentiles and min and max values are similar to the measured data.

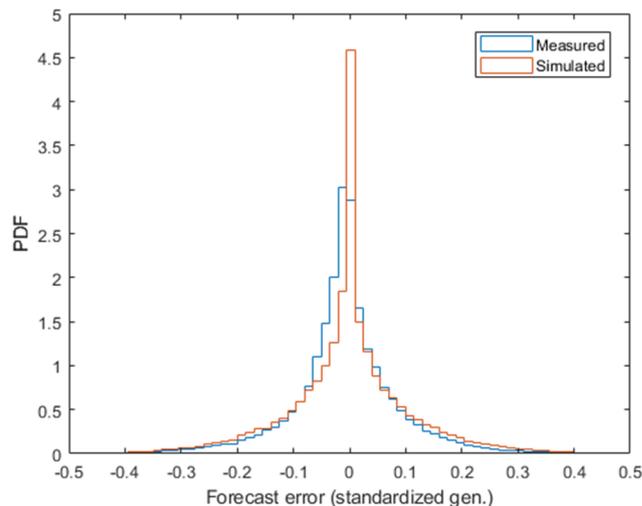


Figure 30. Measured and simulated intraday forecast error PDFs; aggregate of all the OWPPs belonging to validation (BE2018). Data from 2017-2018, when all plants have recordings (only simulations of those time steps where all measurements are available are considered).

Table 15. Intraday forecast error statics for the aggregate of the validation OWPPs (BE 2018).

	mean	SD	min	Prct 0.1	Prct 1	Prct 5	Prct 95	Prct 99	Prct 99.9	max
Measured	-0.007	0.097	-0.735	-0.485	-0.299	-0.167	0.149	0.269	0.469	0.759
CorWind	-0.002	0.112	-0.872	-0.473	-0.322	-0.192	0.188	0.316	0.487	0.638

Data from 2017-2018, when all plants have recordings (only simulations of those time steps where all measurements are available are considered).

6.4.3 Latest forecasts

The “Last” forecasts in Elia’s data denote the latest forecast available for each time step (15 min resolution). Table 16 and Figure 31 compare the measure and simulated latest forecast errors. CorWind shows somewhat lower SD and the most extreme percentiles indicate lower forecast errors in CorWind compared to measurements. However, the PDF looks quite similar for measured and simulated data, and the min and max values are similar. Comparing to Table 15, it can be seen that:

- For the measurement, “Last” shows higher min and max forecast errors compared to Intraday;
- For CorWind, “Last” shows a higher max forecast error compared to Intraday.

It is noted that the measured data shows relatively small decrease in forecast error SD from Intraday to “Last”. In CorWind, this difference is larger.

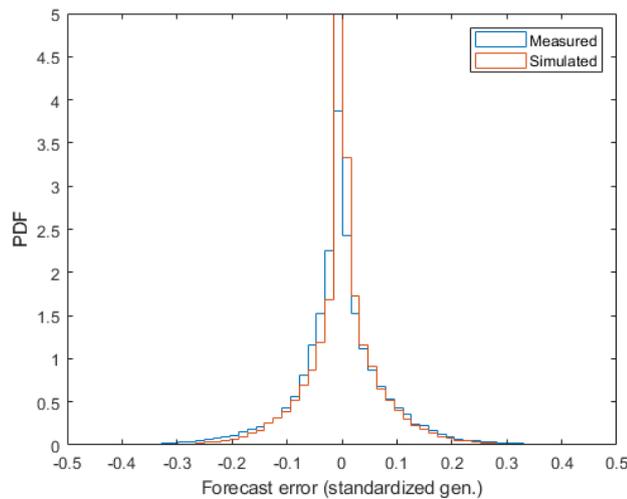


Figure 31. Measured and simulated latest (“Last”) forecast error PDFs; aggregate of all the OWPPs belonging to validation (BE2018). Data from 2017-2018, when all plants have recordings (only simulations of those time steps where all measurements are available are considered).

Table 16. “Last” forecast error statics for the aggregate of the validation OWPPs (BE 2018).

	mean	SD	min	Prct 0.1	Prct 1	Prct 5	Prct 95	Prct 99	Prct 99.9	max
Measured	-0.005	0.087	-0.795	-0.450	-0.261	-0.146	0.135	0.244	0.427	0.765
CorWind	0.001	0.071	-0.798	-0.334	-0.203	-0.117	0.118	0.208	0.346	0.683

Data from 2017-2018, when all plants have recordings (only simulations of those time steps where all measurements are available are considered).

6.5 Conclusion on the model validation

The model validation shows that CorWind is able to model the generation time series of the existing offshore wind power plants in Belgium (the BE2018 OWPPs). It is thus considered valid for modelling the MOG II capacity extension.

The capacity factors predicted by CorWind are slightly larger because the simulations assume 100 % availability. However, availability is not applied as a static factor (e.g., 0.95), because it would change other statistics that are well modelled (e.g., SD). In addition:

- Full installed capacity ramps are seen in data during a few hours;
- The availability factor in the future is unknown, also but not only for the additional installations;
- Overplanting is not to be excluded for the additional installations.

Therefore, it would not be appropriate to include an availability factor for the purposes of this study, nor to post-process the results which would artificially decrease the evaluation of extreme events.

Statistics of ramps are similar for the measured and simulated data. There is a slight underestimation of the 0.1 and 99.9 percentiles; this means that the likelihoods of the events rarer than the 0.1 and 99.9 percentile range may be underestimated in CorWind. However, the simulated data are not adjusted, because the reason for these differences cannot be clearly identified. This needs to be noted when assessing the results of the extended capacity simulations.

The highest wind speed from the mesoscale WRF data are increased by 8 %. This is justified looking at the measured wind speed data, and based on literature on the expected underestimation of maximum wind speeds in WRF. The resulting CorWind runs model well the likelihoods of very high wind speeds. The use of 37 years of meteorological data in the simulation of the extended capacity ensures that a wide range of extreme events are simulated.

For forecast errors, CorWind shows similar statistics compared to measured data. The SDs differ slightly for day-head and intraday; however, percentiles and min and max values are similar. For the “Last” forecast errors, CorWind shows somewhat lower general uncertainty than the measured data; however, min and max values are similar to measurements. In general, forecast errors are more difficult to simulate, as the target is not to replicate the variability due to weather, but to try to represent the forecasts by Elia’s forecast provider. For this reason, the results presented for forecasts and forecast errors for the extended capacity scenarios need to be taken as representing average changes in the forecast errors resulting from different geographical installation distributions and storm shutdown technologies. The actual simulated forecast and forecast error values for an individual event are stochastic, and can be high or low due to randomness.

7. Basic statistics for the scenarios

This chapter presents CFs and SDs for all the scenarios. PDFs are also shown to visualise differences between the scenarios.

7.1 Capacity factors and standard deviations

CFs and SDs of the aggregate generation in the different scenarios are given in Table 17.

It can be seen that the aggregate CF of the fleet is expected to increase from BE 2018 towards the 4.4 GW scenarios, with Tech B showing significant increase compared to Tech A; this leads to more annual offshore generation with the same installed capacity.

The SD increases only slightly towards the 4.4 GW scenarios, with Tech B showing marginally higher SD than Tech A. The 4.4 GW Tech A and B mixture scenarios shows all statistics in between the full Tech A and B scenarios. As storm events are rare, there are only very small difference between the different storm shutdown types for these statistics.

Statistics for the additional installations (instead of the full fleet) are given in Appendix A: CFs and SDs of the additional installations.

Table 17. Capacity factors and standard deviations.

			CF	SD	CF compared to BE 2018	SD compared to BE 2018
BE 2018 (877 MW)			0.420	0.346	100%	100%
2.3 GW			0.430	0.354	103%	102%
3.0 GW	Tech A	25 m/s	0.436	0.353	104%	102%
		Moderate	0.436	0.353	104%	102%
		Deep	0.437	0.353	104%	102%
	Tech B	25 m/s	0.453	0.353	108%	102%
		Moderate	0.454	0.354	108%	102%
		Deep	0.455	0.354	108%	102%
4.0 GW	Tech A	25 m/s	0.447	0.353	106%	102%
		Moderate	0.448	0.354	107%	102%
		Deep	0.448	0.354	107%	102%
	Tech B	25 m/s	0.480	0.356	114%	103%
		Moderate	0.482	0.357	115%	103%
		Deep	0.482	0.357	115%	103%
4.4 GW	Tech A	25 m/s	0.449	0.354	107%	102%
		Moderate	0.450	0.354	107%	102%
		Deep	0.450	0.355	107%	102%
	Tech B	25 m/s	0.485	0.357	116%	103%
		Moderate	0.487	0.358	116%	103%
		Deep	0.488	0.358	116%	103%
Tech A/B	25 m/s	0.474	0.355	113%	103%	
	Moderate	0.475	0.356	113%	103%	
	Deep	0.476	0.356	113%	103%	

From aggregate standardized generation of the 37 years of simulations on 5 min resolution. Tech A/B has mixture of Tech A and Tech B (see Section 4.3). Availability of 100 % is assumed.

7.2 Variability

PDFs of the 4.4 GW Tech A and Tech B scenario generations are shown in Figure 32, with BE 2018 shown for comparison. The Tech B scenarios show increased likelihoods of generation being around 75 % to 100 % of installed capacity and reduced likelihoods of low generation; these differences lead to the increased CF seen in Table 17. Figure 33 shows that storm shutdown type has very limited impact of the generation PDF, as expected (storm events are rare).

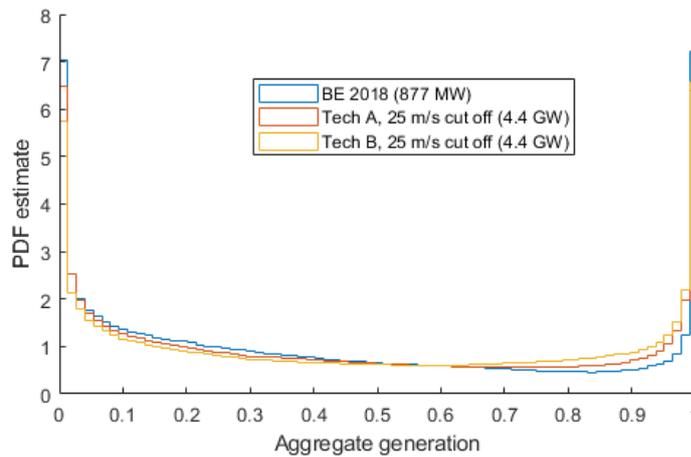


Figure 32. Generation PDFs for BE2018 and 4.4 GW Tech A and Tech B scenarios with direct 25 m/s cut off (standardized generation).

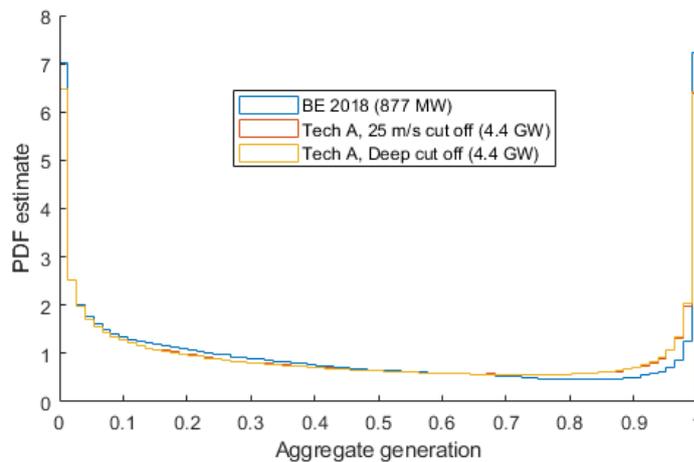


Figure 33. Generation PDFs for BE2018 and 4.4 GW Tech A scenarios with direct 25 m/s and Deep storm shutdown type (standardized generation).

8. Statistical analysis of ramping events

This chapter presents the results on ramping events for the studied scenarios; the scenarios are presented in Section 4.3. 37 years, from 1982 to 2018, are simulated on 5 min resolution. Each OWPP is simulated, although only aggregated ramp results are reported. All results are given based on 5 min resolution data.

The first section compares the scenarios in standardized generation, as the impact of geographical smoothening is easier to see when all data are standardized. The further sections show results in GW.

It is to be noted that the storm events are not filtered out of the data, which means that the ramps that occur during the cut-out and the cut-in phases of storms is included in the statistics presented. In order to isolate the ramp events which are not due to storms, section 8.4 shows the same results but only for those days when the maximum daily wind speeds is below 20 m/s.

Note that when comparing the 2.3 GW part (existing + planned OWPPs) and the 2.1 GW of additional installations to reach the 4.4 GW of offshore wind, the 2.3 GW part is referred to as “existing” and 2.1 GW as “additional” in the figures.

8.1 Results in standardized generation

8.1.1 5 min ramps

Figure 34 shows the 5 min ramp PDFs for some example scenarios. It can be seen that the 5 min ramps expressed in standardized generation decrease from BE 2018 towards the 4.4 GW scenario. The PDFs of the different storm shutdown types show very similar PDFs for the 4.4 GW Tech A scenario; this is because storm events are relatively rare, and differences between the different shutdown types impact only the most extreme tails of the distributions.

5 min ramp statistics of all the scenarios are shown in Table 18. The ramp SD decreases significantly from BE 2018 towards the 4.4 GW scenarios. Tech A and B show similar ramp statistics; however, ramps in the Tech B scenarios are slightly higher. The mixture of Tech A and Tech B shows ramp statistics in-between the fully Tech A and fully Tech B scenarios. The Deep and Moderate storm shutdown types show decreased likelihoods for the most extreme ramps compared to the 25 direct cut-off.

Statistics for the additional installations (instead of the full fleet) are given in Appendix B: 5 min ramp statistics for the additional installations. The results show that the most significant reduction in aggregate ramps is only observed when considering both the 2.3 GW of installations and the additional installations towards 4.4. GW.

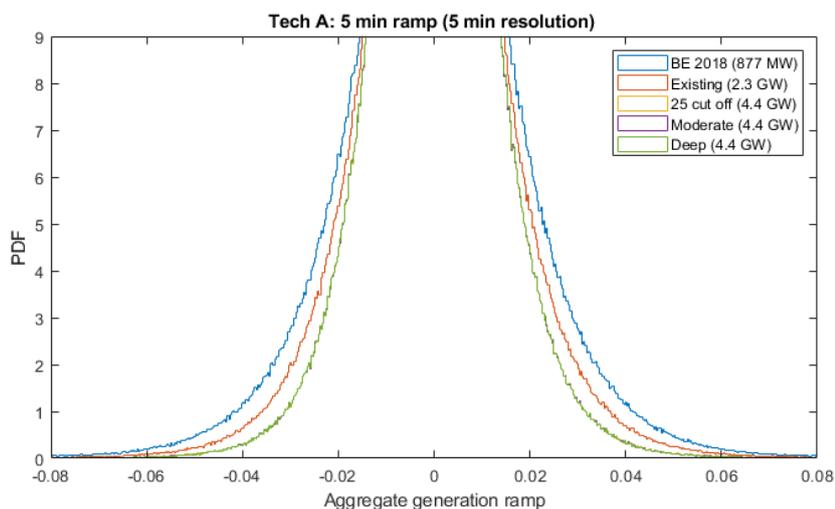


Figure 34. 5 min ramp PDFs for example scenarios (standardized generation). The 4.4 GW scenarios with different storm shutdown types are almost fully on top of each other. “Existing” refers to the 2.3 GW of installations.

Table 18. 5 min ramps statistics (standardized generation).

				Compared to BE 2018							
				SD	Prct 0.01	Prct 0.1	Prct 99.9	Prct 99.99	SD	Prct 0.1	Prct 99.9
BE 2018 (877 MW)				0.015	-0.130	-0.078	0.078	0.136	100%	100%	100%
2.3 GW				0.013	-0.097	-0.061	0.063	0.097	81%	78%	82%
3.0 GW	Tech A	25 m/s	0.012	-0.097	-0.056	0.058	0.098	76%	72%	75%	
		Moderate	0.012	-0.086	-0.055	0.057	0.090	75%	71%	74%	
		Deep	0.012	-0.084	-0.055	0.057	0.087	75%	71%	73%	
	Tech B	25 m/s	0.012	-0.100	-0.057	0.058	0.099	76%	73%	75%	
		Moderate	0.012	-0.089	-0.056	0.057	0.090	75%	72%	74%	
		Deep	0.012	-0.085	-0.055	0.057	0.088	75%	71%	73%	
4.0 GW	Tech A	25 m/s	0.010	-0.096	-0.050	0.052	0.092	68%	64%	66%	
		Moderate	0.010	-0.075	-0.048	0.050	0.079	67%	62%	64%	
		Deep	0.010	-0.071	-0.047	0.049	0.074	66%	61%	63%	
	Tech B	25 m/s	0.011	-0.102	-0.052	0.052	0.099	69%	67%	68%	
		Moderate	0.010	-0.081	-0.050	0.050	0.081	68%	64%	65%	
		Deep	0.010	-0.075	-0.049	0.050	0.077	67%	63%	64%	
4.4 GW	Tech A	25 m/s	0.011	-0.102	-0.050	0.052	0.098	69%	65%	68%	
		Moderate	0.010	-0.077	-0.048	0.050	0.080	67%	62%	65%	
		Deep	0.010	-0.072	-0.048	0.050	0.075	67%	62%	64%	
	Tech B	25 m/s	0.011	-0.110	-0.054	0.054	0.107	70%	69%	69%	
		Moderate	0.011	-0.083	-0.051	0.051	0.084	68%	65%	66%	
		Deep	0.010	-0.076	-0.050	0.050	0.079	68%	64%	65%	
Tech A/B	25 m/s	0.011	-0.106	-0.052	0.053	0.104	69%	68%	68%		
	Moderate	0.010	-0.081	-0.050	0.051	0.082	68%	64%	65%		
		Deep	0.010	-0.075	-0.049	0.050	0.077	68%	63%	64%	

8.1.2 15 min ramps

Figure 35 shows 15 min ramp PDFs for some example scenarios. It can be seen that the 15 min ramps expressed in standardized generation decrease from BE 2018 towards the 4.4 GW of installations. The PDFs of the different storm shutdown types show very similar PDFs; this is because storm events are relatively rare, and differences between the different shutdown types impact only the most extreme tails of the distributions.

15 min ramps statistics of all the scenarios are shown in Table 19. The ramp SD decreases significantly from BE 2018 towards the 4.4 GW scenarios. Tech A and B show similar ramp statistics; still, ramps in the Tech B scenarios are slightly higher. The mixture of Tech A and Tech B shows ramp statistics between the 100% Tech A and 100% Tech B scenarios. The Deep and Moderate storm shutdown types show decreased likelihoods for the most extreme ramps compared to the 25 direct cut-off. It can be seen that the ramp distributions tend to be skewed slightly to the right; this means that there are more extreme up-ramps than down-ramps. This is partly explained by the storm shutdown types only affecting the shutdown and not the restart operation during storm (Section 9.4 provides more information); however, even for non-storm days, up-ramps show slightly higher probability than similar magnitude down-ramps (see Section 8.4).

Statistics for the additional installations (instead of the full fleet) are given in Appendix C: 15 min ramp statistics for the additional installations. The results show that the most significant reduction in aggregate ramps is only observed when considering both the 2.3 GW of installations and the additional installations towards 4.4. GW.

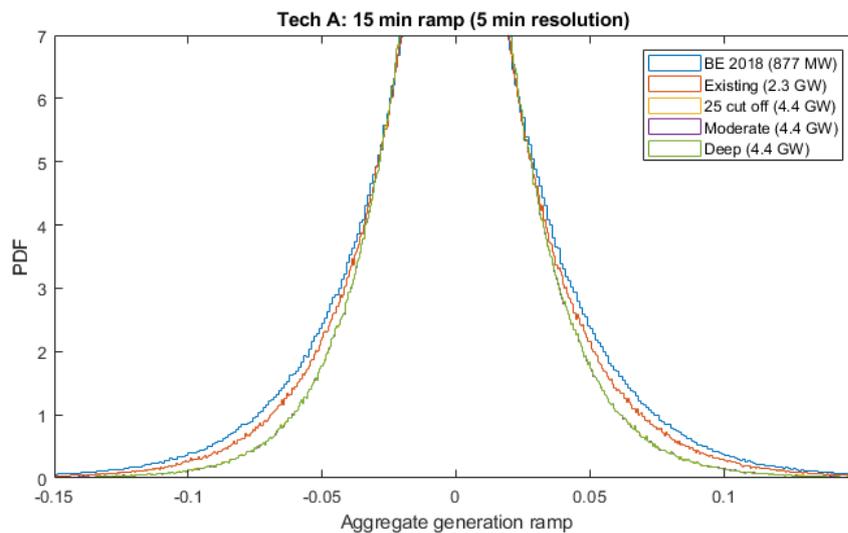


Figure 35. 15 ramp PDFs for example scenarios (standardized generation). The 4.4 GW scenarios with different storm shutdown types are almost fully on top of each other. “Existing” refers to the 2.3 GW of installations.

Table 19. 15 min ramps (5 min resolution) statistics (standardized generation).

						Compared to BE 2018				
		SD	Prct 0.01	Prct 0.1	Prct 99.9	Prct 99.99	SD	Prct 0.1	Prct 99.9	
BE 2018 (877 MW)		0.035	-0.268	-0.171	0.178	0.291	100%	100%	100%	
2.3 GW		0.031	-0.224	-0.147	0.156	0.237	88%	86%	87%	
3.0 GW	Tech A	25 m/s	0.029	-0.222	-0.135	0.145	0.232	81%	79%	81%
		Moderate	0.029	-0.197	-0.132	0.142	0.218	81%	77%	80%
		Deep	0.029	-0.194	-0.131	0.141	0.214	81%	77%	79%
	Tech B	25 m/s	0.029	-0.226	-0.137	0.144	0.232	82%	80%	81%
		Moderate	0.029	-0.203	-0.134	0.141	0.219	81%	78%	79%
		Deep	0.029	-0.197	-0.132	0.139	0.214	81%	77%	78%
4.0 GW	Tech A	25 m/s	0.026	-0.210	-0.123	0.130	0.221	74%	72%	73%
		Moderate	0.026	-0.179	-0.118	0.125	0.198	73%	69%	70%
		Deep	0.026	-0.170	-0.117	0.123	0.186	73%	68%	69%
	Tech B	25 m/s	0.027	-0.222	-0.128	0.131	0.229	75%	75%	73%
		Moderate	0.026	-0.188	-0.122	0.125	0.199	74%	71%	70%
		Deep	0.026	-0.176	-0.120	0.123	0.188	73%	70%	69%
4.4 GW	Tech A	25 m/s	0.026	-0.224	-0.125	0.131	0.230	74%	73%	74%
		Moderate	0.026	-0.181	-0.119	0.126	0.201	73%	70%	71%
		Deep	0.026	-0.170	-0.117	0.124	0.187	73%	69%	69%
	Tech B	25 m/s	0.027	-0.236	-0.131	0.134	0.245	76%	77%	75%
		Moderate	0.026	-0.191	-0.124	0.127	0.206	74%	73%	71%
		Deep	0.026	-0.179	-0.121	0.124	0.191	74%	71%	70%
Tech A/B	25 m/s	0.027	-0.223	-0.129	0.132	0.234	75%	75%	74%	
	Moderate	0.026	-0.187	-0.122	0.125	0.202	74%	71%	70%	
	Deep	0.026	-0.177	-0.120	0.123	0.189	73%	70%	69%	

8.1.3 1 h ramps

Figure 36 shows the 1h ramp PDFs for some example scenarios. It can be seen that the 1 h ramps expressed in standardized generation decrease from BE 2018 towards the 4.4 GW of installations; however, the relative decrease in variability is less than for the 5 min and 15 min ramps. The PDFs of the different storm shutdown types show very similar PDFs for the 4.4 GW scenario.

1h ramp statistics of all scenarios are shown in Table 20. The ramp SD decreases significantly from BE 2018 towards the 4.4 GW scenarios. Tech A and B show similar ramp statistics; however, ramps in the Tech B scenarios are slightly higher. The mixture of Tech A and Tech B shows ramp statistics in between the fully Tech A and fully Tech B scenarios. Unlike for the 5 and 15 min ramps, the Deep and Moderate storm shutdown types show only marginally decreased likelihoods for the most extreme ramps compared to the 25 direct cut-off. It can be seen that the ramp distributions tend to be skewed slightly to the right; this means that there are more extreme up-ramps than down-ramps.

Statistics for the additional installations (instead of the full fleet) are given in Appendix D: 1h ramp statistics for the additional installations. The results show that the most significant reduction in

aggregate ramps is only observed when considering both the 2.3 GW of installations and the additional installations towards 4.4. GW.

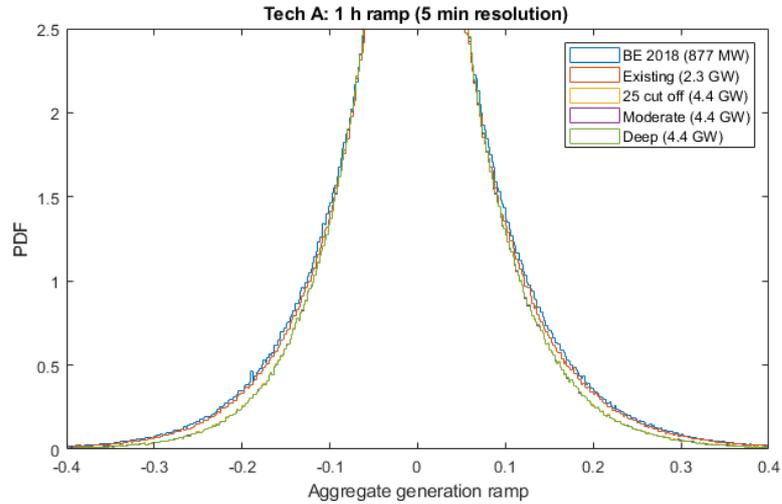


Figure 36. 1h ramp PDFs for example scenarios (standardized generation). The 4.4 GW scenarios with different storm shutdown types are almost fully on top of each other. “Existing” refers to the 2.3 GW of installations.

Table 20. 1 h ramp (5 min resolution) statistics (standardized generation).

				Compared to BE 2018							
				SD	Prct 0.01	Prct 0.1	Prct 99.9	Prct 99.99	SD	Prct 0.1	Prct 99.9
BE 2018 (877 MW)				0.092	-0.604	-0.425	0.463	0.732	100%	100%	100%
2.3 GW				0.088	-0.561	-0.395	0.434	0.629	96%	93%	94%
3.0 GW	Tech A	25 m/s	0.084	-0.522	-0.370	0.411	0.597	91%	87%	89%	
		Moderate	0.083	-0.522	-0.370	0.409	0.596	91%	87%	88%	
		Deep	0.083	-0.522	-0.367	0.407	0.592	90%	86%	88%	
	Tech B	25 m/s	0.083	-0.531	-0.371	0.404	0.579	91%	87%	87%	
		Moderate	0.083	-0.528	-0.372	0.404	0.580	90%	88%	87%	
		Deep	0.083	-0.527	-0.371	0.401	0.578	90%	87%	87%	
4.0 GW	Tech A	25 m/s	0.079	-0.520	-0.362	0.391	0.583	86%	85%	84%	
		Moderate	0.078	-0.504	-0.350	0.382	0.572	85%	82%	83%	
		Deep	0.078	-0.488	-0.342	0.374	0.543	85%	81%	81%	
	Tech B	25 m/s	0.080	-0.516	-0.372	0.390	0.570	86%	88%	84%	
		Moderate	0.079	-0.508	-0.360	0.379	0.563	85%	85%	82%	
		Deep	0.078	-0.500	-0.352	0.371	0.549	85%	83%	80%	
4.4 GW	Tech A	25 m/s	0.079	-0.541	-0.366	0.393	0.600	86%	86%	85%	
		Moderate	0.078	-0.511	-0.351	0.383	0.577	85%	83%	83%	
		Deep	0.078	-0.489	-0.343	0.375	0.544	85%	81%	81%	
	Tech B	25 m/s	0.080	-0.537	-0.380	0.397	0.588	87%	89%	86%	
		Moderate	0.079	-0.521	-0.363	0.382	0.576	86%	86%	83%	
		Deep	0.078	-0.503	-0.354	0.374	0.553	85%	83%	81%	
	Tech A/B	25 m/s	0.079	-0.537	-0.370	0.388	0.589	86%	87%	84%	
		Moderate	0.078	-0.511	-0.357	0.377	0.570	85%	84%	81%	
		Deep	0.078	-0.493	-0.350	0.368	0.547	85%	82%	80%	

8.2 On the scenario with a mixture of Tech A and Tech B

The ramp rate distributions for the Tech A/B scenario for the BE 4.4 GW showed result in between the fully Tech A and fully Tech B scenarios. Thus, it was considered that analysing such mixed technology scenario does not provide any additional insight compared to analysing only the 100% Tech A and 100 % Tech B scenarios. The Tech A/B scenario is not included in the result presented later in the report.

8.3 Results in GW

This section describes the ramp rate results in GW. The simulated data is the same as in Section 8.1. The data are presented looking at the average number of days per year with at least one ramp event more extreme than a given value expressed in GW.

8.3.1 5 min ramps

Table 21 shows the average number of days per year with at least one ramp event more extreme than the given GW value for 5 min ramps. The differences between the scenarios are the same as discussed in Section 8.1.1, but here the scenarios with more installed GW of course show more extreme ramps.

Table 21. 5 min ramps: average number of days per year with at least one event more extreme than the limit.

			Negative ramp (GW)							Positive ramp (GW)									
			4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5
BE 2018 (877 MW)										0.2	0.4	0.1							
Existing (2.3 GW)									0.0	1.5	1.6	0.0							
3.0 GW	Tech A	25 m/s							1.6	7.6	7.7	1.4							
		Moderate							0.3	3.9	4.4	0.4							
		Deep							0.1	3.2	3.8	0.2							
	Tech B	25 m/s							1.9	9.1	8.1	1.5							
		Moderate							0.4	5.1	4.6	0.4							
		Deep							0.1	3.8	3.6	0.3							
4.0 GW	Tech A	25 m/s						0.1	3.9	13.6	13.0	3.4	0.1						
		Moderate							0.6	8.2	8.4	1.0	0.0						
		Deep							0.1	6.3	6.7	0.4							
	Tech B	25 m/s						0.1	4.2	17.2	16.0	4.0	0.1						
		Moderate							1.0	10.5	9.9	1.2	0.0						
		Deep							0.1	8.1	8.1	0.7							
4.4 GW	Tech A	25 m/s						0.4	5.9	19.1	19.1	5.1	0.4						
		Moderate						0.0	1.3	13.2	13.9	1.8	0.1						
		Deep							0.5	11.0	12.1	0.9	0.0						
	Tech B	25 m/s						0.3	7.5	24.3	23.6	6.3	0.3	0.0					
		Moderate							2.2	17.1	16.9	2.3	0.2						
		Deep							0.7	14.1	14.6	1.2	0.1						

“Existing” refers to the 2.3 GW of installations.

8.3.2 15 min ramps

Table 22 shows the average number of days per year with at least one ramp event more extreme than the given GW value for 15 min ramps (on 5 min resolution). The differences between the scenarios are the same as discussed in Section 8.1.2, but here the scenarios with more installed

GW of course show more extreme ramps. The tendency of the ramp PDF to be skewed slightly to the right is seen as higher number of events for example 2 GW up-ramps than 2 GW down-ramps (negative ramps). This is discussed further in Section 8.4 and Section 9.4.

Table 22. 15 min ramps: average number of days per year with at least one event more extreme than the limit.

		Negative ramp (GW)									Positive ramp (GW)								
		4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0
BE 2018 (877 MW)								0.4	1.9	2.4	0.4								
Existing (2.3 GW)								6.5	70.7	82.4	8.3	0.1							
3.0 GW	Tech A	25 m/s						0.1	17.4	126.3	140.5	21.1	0.4	0.1					
		Moderate						0.1	13.8	123.2	137.9	17.9	0.3						
		Deep						0.1	12.8	122.4	137.0	17.0	0.3						
	Tech B	25 m/s						0.1	18.2	129.5	138.9	21.7	0.4	0.0					
		Moderate						0.1	14.6	125.2	135.1	18.0	0.4						
		Deep						0.1	13.2	124.0	133.9	16.7	0.4	0.1					
4.0 GW	Tech A	25 m/s					0.6	2.8	35.2	191.3	198.9	38.6	2.7	0.5	0.1	0.0			
		Moderate					0.0	0.5	30.8	188.1	195.5	34.5	1.3	0.3	0.1				
		Deep					0.3	28.9	187.3	194.7	32.9	0.6	0.1	0.0					
	Tech B	25 m/s					0.5	3.3	40.6	199.6	203.5	41.9	3.4	0.6	0.2				
		Moderate					0.0	0.8	34.6	194.6	199.1	36.5	1.5	0.3	0.1				
		Deep					0.2	32.4	193.4	198.0	34.5	0.8	0.2	0.0					
4.4 GW	Tech A	25 m/s				0.3	1.2	4.4	53.6	227.1	232.9	59.3	4.5	1.2	0.3	0.1			
		Moderate					0.2	1.3	48.9	223.9	229.6	55.0	2.3	0.5	0.1	0.0			
		Deep					0.6	47.0	223.4	228.9	53.2	1.3	0.1	0.0					
	Tech B	25 m/s				0.2	1.5	5.5	64.1	234.9	239.6	64.0	5.7	1.3	0.4	0.1			
		Moderate				0.3	2.1	58.1	230.2	235.2	58.0	2.7	0.5	0.2	0.0				
		Deep				0.1	1.1	55.6	229.6	234.0	56.0	1.8	0.3	0.0	0.0				

“Existing” refers to the 2.3 GW of installations.

8.3.3 1 h ramps

Table 23 shows the average number of days per year with at least one ramp event more extreme than the given GW value for 1 h ramps (on 5 min resolution). The differences between the scenarios are the same as discussed in Section 8.1.3, but here the scenarios with more installed GW of course show more extreme ramps. The tendency of the ramp PDF to be skewed slightly to the right shows a higher number of events for example 2 GW up-ramps than 2 GW down-ramps. This is discussed further in Section 8.4 and Section 9.4.

Table 23. 1 h ramps: average number of days per year with at least one event more extreme than the limit.

		Negative ramp (GW)								Positive ramp (GW)										
		4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	
BE 2018 (877 MW)									4.2	57.2	65.3	7.5								
Existing (2.3 GW)						0.1	0.8	12.8	176.5	286.6	285.9	182.8	19.0	1.7	0.2					
3.0 GW	Tech A	25 m/s				0.1	0.4	3.3	33.4	229.8	308.0	305.5	233.9	45.3	6.6	0.9	0.2			
		Moderate				0.1	0.4	3.3	32.8	227.7	306.9	304.1	232.0	44.8	6.5	1.0	0.2			
		Deep				0.1	0.4	3.2	32.1	227.3	306.8	303.9	231.5	43.7	6.3	0.9	0.2			
	Tech B	25 m/s				0.1	0.5	3.5	34.1	233.3	310.7	308.4	236.1	44.1	5.8	0.9	0.2			
		Moderate				0.1	0.5	3.4	33.8	230.2	308.5	306.3	233.4	43.7	5.8	0.9	0.2			
		Deep				0.1	0.5	3.4	33.1	229.6	308.5	305.9	232.6	42.8	5.7	0.9	0.2			
4.0 GW	Tech A	25 m/s			0.1	0.4	2.9	13.9	77.5	267.6	322.3	319.5	268.9	91.5	20.1	5.1	1.2	0.3	0.1	
		Moderate			0.1	0.4	2.2	11.8	74.7	265.2	320.9	317.9	266.6	88.9	18.4	4.2	1.2	0.3	0.1	
		Deep			0.1	0.4	1.8	10.7	73.7	264.7	320.8	317.7	266.3	87.6	17.2	3.4	0.8	0.2	0.1	
	Tech B	25 m/s			0.1	0.5	3.2	17.1	83.0	272.3	325.4	323.9	273.6	90.9	20.4	4.5	1.0	0.2	0.1	
		Moderate			0.1	0.5	2.7	14.7	78.9	268.5	322.9	321.7	270.0	87.1	17.6	4.0	1.0	0.3	0.1	
		Deep			0.1	0.5	2.2	13.3	77.5	267.9	322.7	321.3	269.3	85.6	16.4	3.3	0.8	0.2	0.1	
4.4 GW	Tech A	25 m/s			0.2	1.6	6.3	21.9	105.4	282.8	328.1	325.7	282.5	118.1	30.4	8.6	3.0	0.7	0.2	0.1
		Moderate			0.2	0.9	4.4	19.6	102.3	280.4	326.6	324.1	280.2	115.4	28.0	7.1	2.2	0.6	0.2	0.1
		Deep			0.2	0.8	3.5	18.1	101.4	280.1	326.6	323.9	279.9	114.2	26.6	6.0	1.6	0.3	0.1	0.1
	Tech B	25 m/s			0.2	1.4	7.5	26.7	114.2	286.7	330.9	329.8	288.4	121.7	32.1	8.9	2.5	0.6	0.2	0.1
		Moderate		0.0	0.2	1.0	5.1	23.6	109.8	283.0	328.5	327.6	284.7	117.6	28.7	6.9	2.2	0.7	0.2	0.1
		Deep			0.2	1.0	4.1	22.0	108.3	282.4	328.5	327.4	284.1	116.1	27.0	5.7	1.6	0.5	0.2	0.1

“Existing” refers to the 2.3 GW of installations.

8.4 Ramps when daily max wind speed is low

The previous section has shown expected ramp event likelihoods when considering all the simulated days. This section shows the likelihoods when considering only days when the maximum daily wind speeds (fleet-level mean, weighted by installed capacity) is below 20 m/s. Such days cover approximately 92 % of all the simulated days.

Looking at the 1 h ramp events on the days with maximum wind speed below 20 m/s in Table 24 and comparing to Table 23, it can be seen that the most extreme up-ramps are unlikely to happen on days without high wind speed. However, a single up-ramp event higher than 4 GW in the 4.4. GW scenarios occurs during a day without maximum wind speed above 20 m/s. This event is plotted for the BE 4.4 GW Tech A scenarios in Figure 37; the same date caused also the extreme up-ramp for the Tech B scenarios. This shows that extreme ramps can happen also without a storm; however, such extreme event happened only once during the 37 years of simulations (5 min resolution). The single event visualised in Figure 37 is the cause for having an event with higher than 3.5 and 4 GW up-ramp in Table 24. Even though this extreme event is an up-ramp event, it is possible that also an extreme down-ramp event can happen in the future. Up- and down-ramp probabilities are compared for storm days in Section 9.3.

Next to these most extreme events, the results for 4.4GW installed capacity in Table 24 show that ramps of more than 2 GW in 1 hour are to be expected approximately 3 days a year for down-ramps and 4 days a year for up-ramps. And ramps > 2.5 GW less than 1 day a year for down-

ramps and around 1 day a year for up-ramps and, on average. These results are for days with max wind speed below 20 m/s; results for storm-days are presented in Section 9.3.

The 5 min and 15 min ramp event tables for days with maximum wind speed below 20 m/s are shown in Appendix E: 5 min ramp statistics for days with maximum wind speed below 20 m/s and Appendix F: 15 min ramp statistics for days with maximum wind speed below 20 m/s. The numbers show that the highest 5 and 15 min ramps do not tend to occur on days without a high wind speed (> 20 m/s).

Table 24. 1 h ramps: average number of days per year with at least one event when the daily max fleet-level wind speed is below 20 m/s.

		Negative ramp (GW)									Positive ramp (GW)								
		4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0
BE 2018 (877 MW)									2.8	49.9	56.1	4.6							
Existing (2.3 GW)					0.1	0.5	11.2	163.9	266.4	265.3	168.7	16.1	1.1	0.1					
3.0 GW	Tech A	25 m/s			0.0	0.3	2.6	28.4	212.1	285.2	282.2	215.1	38.4	4.8	0.5	0.1			
		Moderate			0.0	0.3	2.6	28.4	212.1	285.2	282.2	215.0	38.4	4.8	0.5	0.1			
		Deep			0.0	0.3	2.6	28.4	212.1	285.2	282.2	215.0	38.4	4.8	0.5	0.1			
	Tech B	25 m/s			0.1	0.3	2.7	29.3	214.2	286.5	283.6	215.8	37.3	4.3	0.5	0.1			
		Moderate			0.1	0.3	2.7	29.3	214.1	286.5	283.6	215.6	37.3	4.3	0.5	0.1			
		Deep			0.1	0.3	2.7	29.3	214.1	286.5	283.6	215.6	37.3	4.3	0.5	0.1			
4.0 GW	Tech A	25 m/s		0.1	0.3	1.5	9.1	67.2	248.2	299.0	295.9	248.5	79.4	14.1	2.6	0.5	0.1	0.0	
		Moderate		0.1	0.3	1.5	9.1	67.2	248.1	299.0	295.9	248.4	79.4	14.1	2.6	0.5	0.1	0.0	
		Deep		0.1	0.3	1.5	9.1	67.2	248.1	299.0	295.9	248.4	79.4	14.1	2.6	0.5	0.1	0.0	
	Tech B	25 m/s		0.1	0.4	1.9	11.4	70.9	251.0	299.9	298.0	251.6	77.5	13.8	2.3	0.3	0.0	0.0	
		Moderate		0.1	0.4	1.9	11.4	70.9	250.9	299.9	297.9	251.5	77.4	13.7	2.2	0.3	0.0	0.0	
		Deep		0.1	0.4	1.9	11.4	70.9	250.9	299.9	297.9	251.5	77.4	13.7	2.2	0.3	0.0	0.0	
4.4 GW	Tech A	25 m/s		0.1	0.6	2.9	15.8	93.3	262.2	304.1	301.5	261.1	104.1	22.6	4.6	1.1	0.1	0.0	0.0
		Moderate		0.1	0.6	2.9	15.8	93.2	262.2	304.1	301.5	261.1	104.1	22.5	4.6	1.1	0.1	0.0	0.0
		Deep		0.1	0.6	2.9	15.8	93.2	262.2	304.1	301.5	261.1	104.1	22.5	4.6	1.1	0.1	0.0	0.0
	Tech B	25 m/s		0.1	0.7	3.4	19.1	100.2	264.4	304.5	303.1	265.2	106.3	23.4	4.2	0.8	0.2	0.0	0.0
		Moderate		0.1	0.7	3.4	19.1	100.1	264.3	304.5	303.0	265.1	106.2	23.2	4.2	0.8	0.2	0.0	0.0
		Deep		0.1	0.7	3.4	19.1	100.1	264.3	304.5	303.0	265.1	106.2	23.2	4.2	0.8	0.2	0.0	0.0

Days with maximum fleet-level wind speed below 20 m/s cover approximately 92 % of the simulated days (small differences between the scenarios). “Existing” refers to the 2.3 GW of installations.

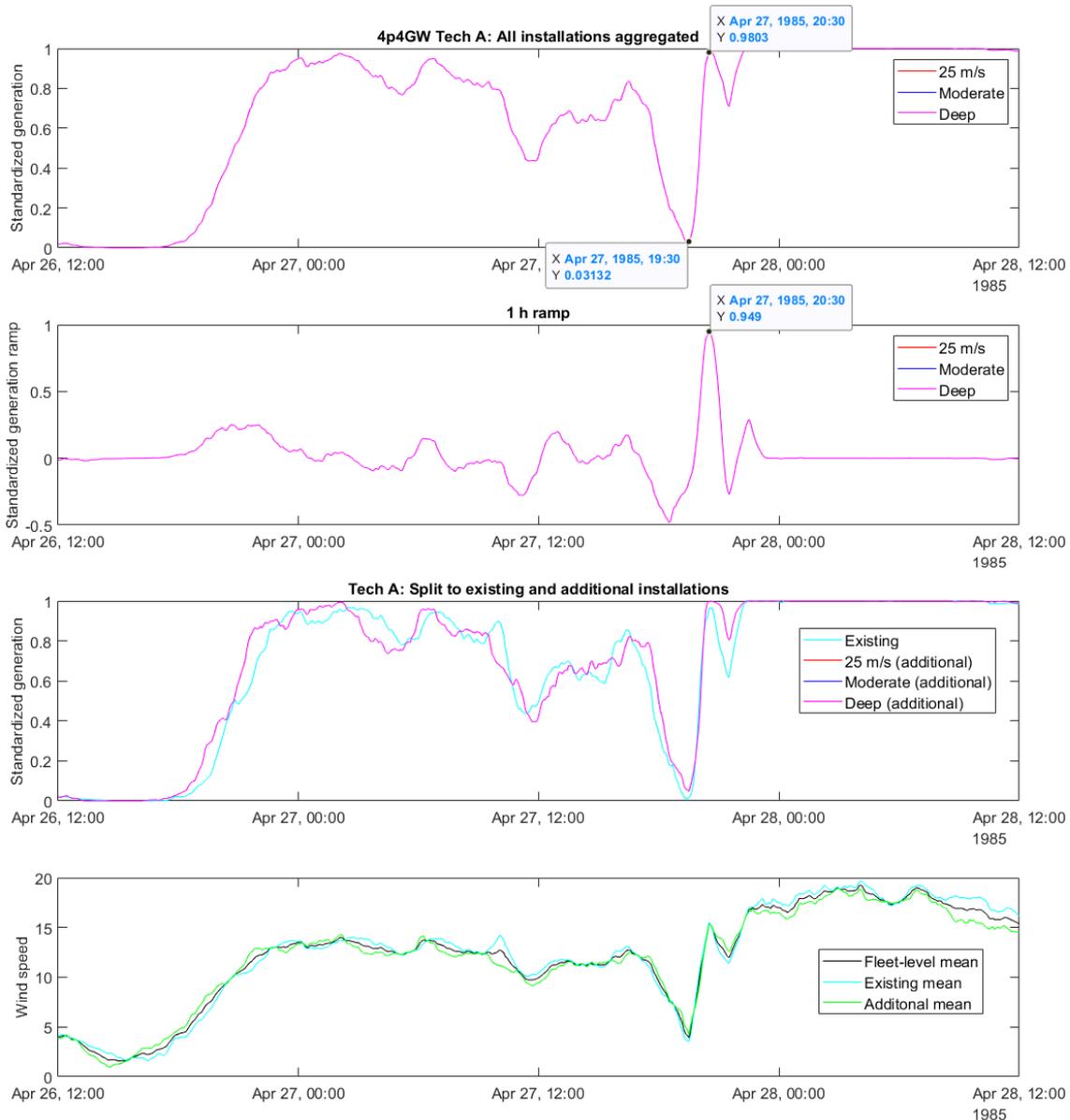


Figure 37. The most extreme up-ramp event for the BE 4.4 GW Tech A scenario when considering days with max wind speed below 20 m/s. As wind speeds are < 20 m/s, all storm shutdown types show the same generation time series. “Existing” refers to the 2.3 GW of installations and “additional” to the 2.1 GW of additional installation to reach 4.4. GW.

8.5 Conclusions on ramps

Considering standardized generation, ramps are expected to be reduced towards the 4.4 GW of installations. This is caused by geographical smoothing. 5 min ramps are reduced more than 1 h ramps. However, when expressed in GW, ramps are expected to increase significantly in the future. In the 4.4 GW scenarios, ramps of more than 2 GW in 1 hour are expected to occur multiple times in a year. 1 hour down-ramp larger than 2.5 GW is expected on approximately one day in a year, and 1 hour up-ramp of more than 2.5 GW approximately on 2 or 3 days a year. Extreme up-ramps are more likely than similar size down-ramps (this is discussed more in Section 9.4).

The results show that the highest 5 and 15 min ramps do not tend to occur on days without a high wind speed (fleet-level mean wind speed > 20 m/s). However, even for non-storm days, an up-ramp larger than 4 GW within 1 hour (5 min resolution) was seen once in the simulation for the 4.4 GW scenarios. This shows that the most extreme ramps are possible also on non-storm days, but they are unlikely. Even though similar size down-ramp was not seen in the simulations, it cannot be ruled out that such down-ramp events could not happen in the future. However, generally, extreme ramps tend to occur more on storm days, as presented in section 9.

As described in Section 6.5, unavailability is not modelled (100 % availability is assumed). It is important to note that the likelihoods of the most extreme ramp events may be slightly underestimated, based on the comparison between measured and simulated data in Section 6.

9. Statistical analysis of storm events

This chapter presents statistics of storm events in the simulated 37 years of data. Both the likelihoods of fleet-wide shutdowns and ramping during high wind speed days are reported. All results are given based on 5 min resolution data.

Note that when comparing the 2.3 GW part (existing + planned OWPPs) and the 2.1 GW of additional installations to reach the 4.4 GW of offshore wind, the 2.3 GW part is referred to as “existing” and 2.1 GW as “additional” in the figures.

9.1 Simulated 37 years of wind speeds

Simulated fleet-level wind speeds for the BE 4.4 GW Tech A scenario can be seen in Figure 38. The highest fleet-level wind speeds reach approximately 35 m/s (5 min resolution); highest plant-level wind speeds are even higher. It can be observed that high wind speeds occur throughout the 37 years; however, the latest few years up to 2018 do not show very high wind speed peaks, meaning that the most extreme weather conditions have not yet been experienced by the offshore wind parks. Tech B shows slightly higher fleet-level wind speeds due to additional installations having higher hub heights.

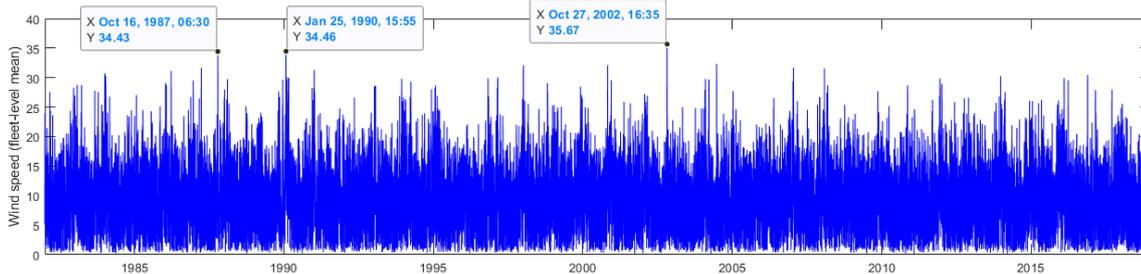


Figure 38. Effective fleet-level wind speeds (weighted by OWPP installed capacity) in the BE 4.4 GW Tech A scenario (5 min resolution). Time series are until the end of 2018; some of the highest peaks are marked.

9.2 Generation during storms

Example time series around the 1990 extreme high wind speed event (as seen in Figure 38) can be seen in Figure 39. With such high wind speeds, the entire fleet (4.4 GW) is in shutdown for some hours with all the scenarios considered. In this specific example, the Moderate and Deep types show smoother ramping than the 25 direct cut-off; however, on the aggregate 4.4 GW level (top subplot), they all reach zero generation at the same time. The 2.3 GW of installations (existing) show smooth shutdown behaviour, because some OWPPs have a higher than 25 m/s cut-off limit and many OWPPs have the Deep shutdown behaviour also in the 2.3 GW of installations (middle subplot). The 2.3 GW (existing) shut down later than the Deep additional 2.1 GW of installations because wind speeds in the 2.3 GW installation locations increase later and up to a lower maximum level than in the additional 2.1 GW locations (bottom subplot).

Figure 40 shows that even with the Deep shutdown type, the 4.4 GW Tech A scenario is expected to sometimes experience a full shut-down. Figure 41 shows that the storm shut down type does not have a significant impact on the number of occurrences where the entire fleet experiences a

total shut-down; although the Deep types shows slightly less shut-down hours. These observations are in line with the case plotted in Figure 39. However, Figure 39 also suggest that there are differences in ramping during storm events for the different shutdown types; this is investigated in the following sections. And the shutdown type impacts the expected number of shut-down hours per year for the additional (2.1 GW) part of the installations: see Appendix G: Number of hours per year in full shut-down (additional 2.1 GW only).

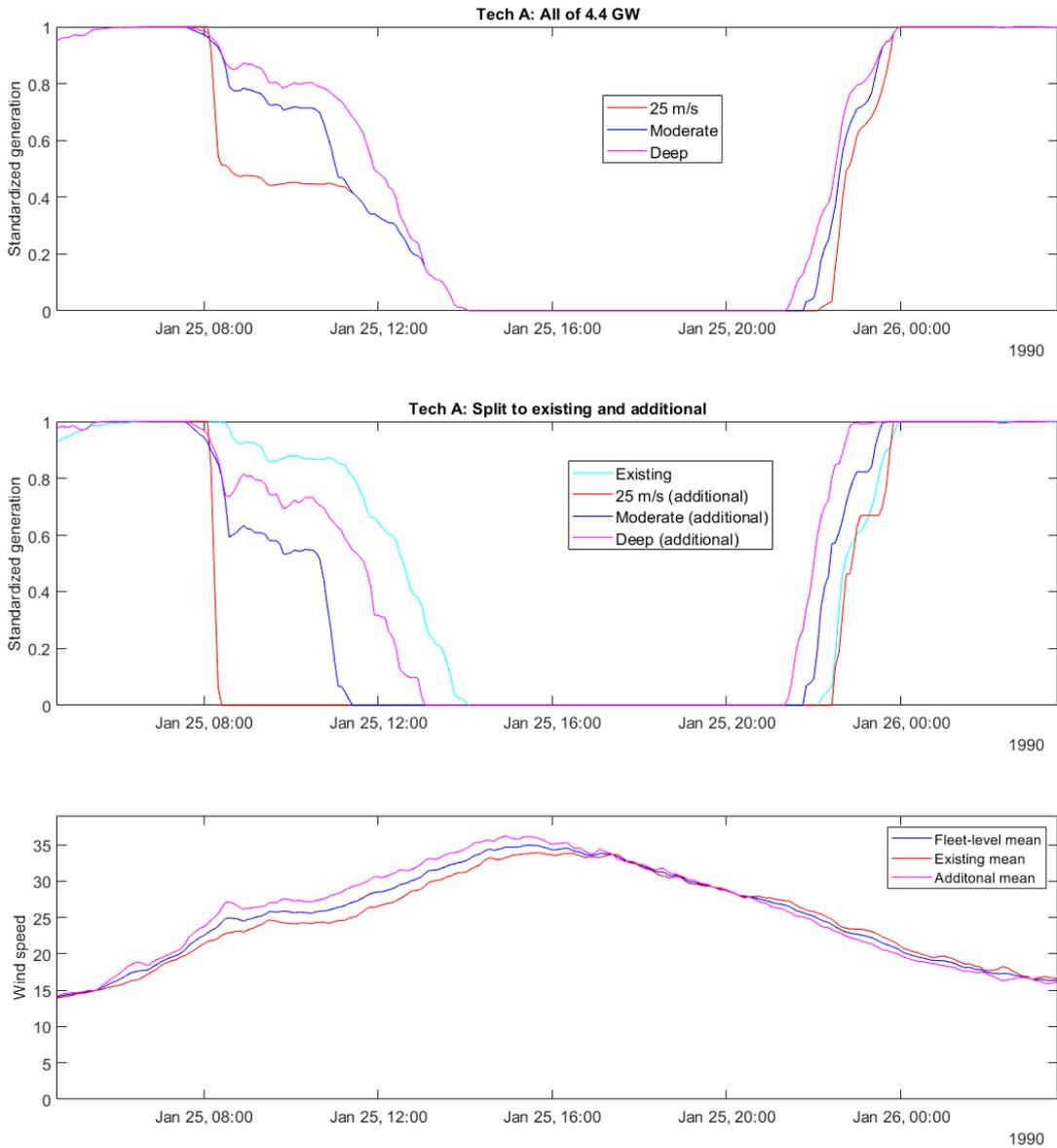


Figure 39. Example extreme storm case for the BE 4.4 GW Tech A scenario: all storm shutdown types plotted. “Existing” refers to the 2.3 GW of installations and “additional” to the 2.1 GW of additional installation to reach 4.4 GW.

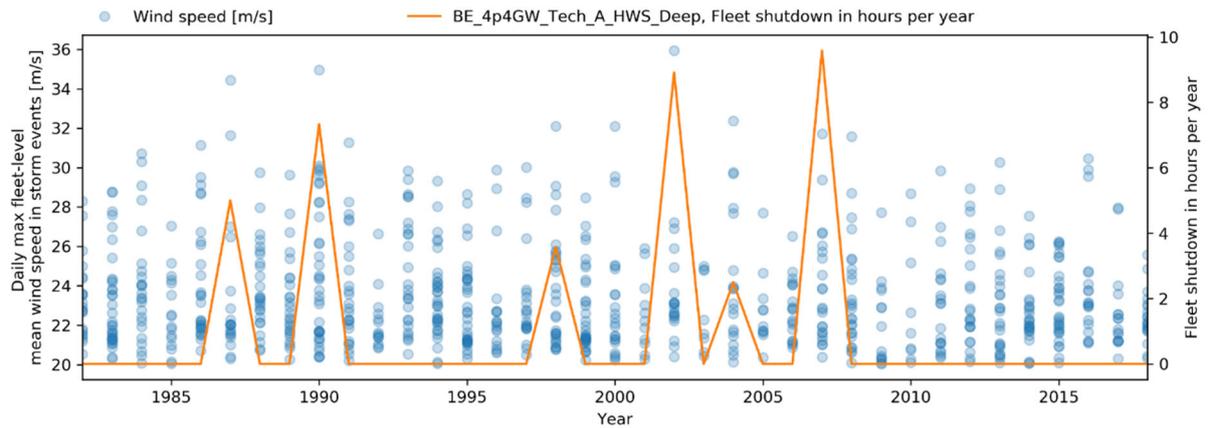


Figure 40. Number of hours when the entire fleet is in shutdown (aggregate generation zero) per year for the BE 4.4 GW Tech A Deep storm shutdown scenario.

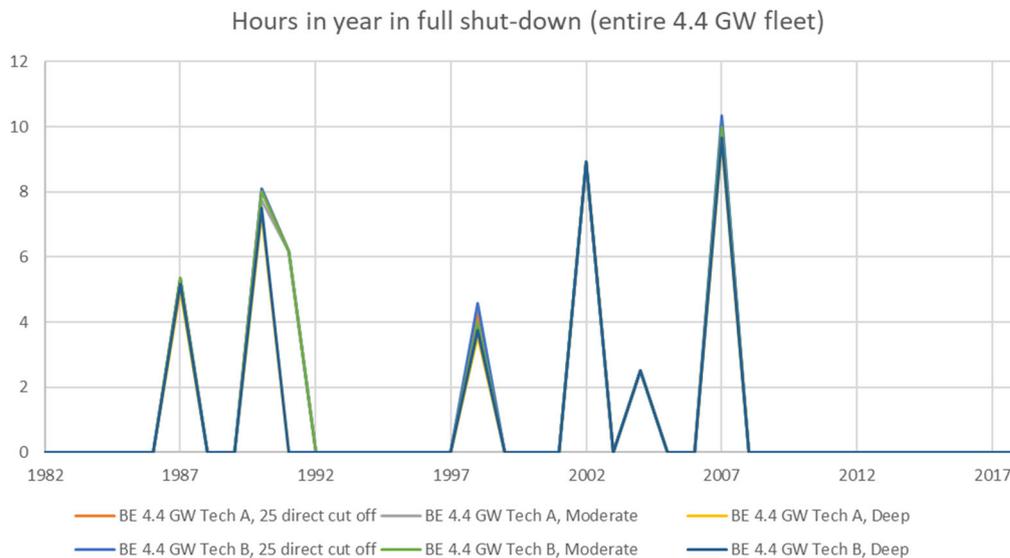


Figure 41. Number of hours when the entire fleet is in shut-down (aggregate generation zero) per year for the 4.4 GW scenarios. Full shut-down occurs in 6 or 7 of the 37 simulated years.

9.3 Ramps during high wind speed days

9.3.1 5 min ramps

Table 25 shows the average number of days per year with at least one ramp event more extreme than the given GW limit for 5 min ramps for those days when the daily max wind speed is above 20 m/s. Comparing to Table 21 (which considers all simulated days) and Appendix E: 5 min ramp statistics for days with maximum wind speed below 20 m/s, it can be seen that most days with extreme 5 min ramps occur on high wind days. Table 25 shows that the Deep type shows significantly reduced likelihoods for extreme ramps compared to direct 25 cut-off.

Table 25. 5 min ramps: average number of days per year with at least one event more extreme than the limit for days with max fleet-level wind speed above 20 m/s.

		Negative ramp (GW)									Positive ramp (GW)								
		4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0
BE 2018 (877 MW)										0.2	0.4	0.1							
Existing (2.3 GW)										0.6	0.7	0.0							
3.0 GW	Tech A	25 m/s							1.2	5.0	4.9	0.9							
		Moderate							0.2	1.6	1.9	0.3							
		Deep							0.1	1.0	1.4	0.1							
	Tech B	25 m/s							1.4	6.0	5.6	1.1							
		Moderate							0.3	2.4	2.5	0.4							
		Deep							0.1	1.1	1.5	0.2							
4.0 GW	Tech A	25 m/s						0.1	3.3	7.9	7.3	2.8	0.1						
		Moderate							0.6	3.2	3.5	0.8	0.0						
		Deep							0.1	1.5	1.9	0.3							
	Tech B	25 m/s						0.1	3.5	10.0	9.1	3.3	0.1						
		Moderate							0.9	4.2	3.9	0.9	0.0						
		Deep							0.1	1.8	2.2	0.5							
4.4 GW	Tech A	25 m/s						0.4	4.9	9.2	9.0	4.1	0.4						
		Moderate						0.0	1.1	4.1	4.5	1.4	0.1						
		Deep							0.2	2.0	2.7	0.5	0.0						
	Tech B	25 m/s						0.2	6.2	11.8	11.2	5.1	0.3	0.0					
		Moderate							1.7	5.4	5.4	1.8	0.2						
		Deep							0.2	2.5	3.2	0.8	0.1						

Days with maximum fleet-level wind speed above 20 m/s cover approximately 8 % of the simulated days (small differences between the scenarios). “Existing” refers to the 2.3 GW of installations.

9.3.2 15 min ramps

Table 26 shows the average number of days per year with at least one ramp event more extreme than the given GW limit for 15 min ramps for those days when the daily max wind speed is above 20 m/s. Comparing to Table 22 (which considers all simulated days) and Appendix F: 15 min ramp statistics for days with maximum wind speed below 20 m/s, it can be seen that most days with extreme 15 min ramps occur on high wind days. Table 26 shows that the Deep type shows significantly reduced likelihoods for extreme ramps compared to direct 25 cut-off, especially on down-ramps. The number of extreme up-ramp events is also reduced, but not as much; this is discussed more in Section 9.4.

Table 26. 15 min ramps: average number of days per year with at least one event more extreme than the limit for days with max fleet-level wind speed above 20 m/s.

		Negative ramp (GW)								Positive ramp (GW)								
		4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5
BE 2018 (877 MW)								0.4	1.4	2.1	0.4							
Existing (2.3 GW)								0.8	7.2	9.4	1.8	0.1						
3.0 GW	Tech A	25 m/s						0.1	6.1	14.4	16.3	7.1	0.4	0.1				
		Moderate						0.1	2.9	11.5	13.8	4.2	0.3					
		Deep						0.1	1.9	10.7	12.9	3.3	0.2					
	Tech B	25 m/s						0.1	6.7	16.2	17.5	8.1	0.4	0.0				
		Moderate						0.1	3.5	12.2	13.9	4.8	0.4					
		Deep						0.1	2.1	11.0	12.7	3.6	0.4	0.1				
4.0 GW	Tech A	25 m/s					0.6	2.6	9.4	17.8	19.1	10.1	2.6	0.5	0.1	0.0		
		Moderate					0.0	0.4	5.5	14.6	15.8	6.5	1.2	0.2	0.1			
		Deep						0.2	3.7	13.9	15.0	4.9	0.5	0.1	0.0			
	Tech B	25 m/s					0.5	3.1	11.7	19.6	20.4	11.8	3.3	0.5	0.2			
		Moderate					0.0	0.7	6.2	14.9	16.3	7.0	1.3	0.3	0.1			
		Deep						0.1	4.0	13.7	15.2	5.1	0.7	0.2	0.0			
4.4 GW	Tech A	25 m/s				0.3	1.2	3.9	11.3	19.4	20.4	12.2	3.9	1.1	0.3	0.1		
		Moderate					0.2	0.9	7.0	16.3	17.2	8.5	1.7	0.5	0.1	0.0		
		Deep						0.2	5.2	15.8	16.5	6.8	0.8	0.1	0.0			
	Tech B	25 m/s				0.2	1.5	4.6	13.6	21.2	21.6	14.1	4.8	1.3	0.4	0.1		
		Moderate					0.3	1.3	8.1	16.6	17.4	8.8	1.9	0.5	0.2	0.0		
		Deep					0.0	0.3	5.7	16.0	16.2	6.8	1.0	0.3	0.0	0.0		

Days with maximum fleet-level wind speed above 20 m/s cover approximately 8 % of the simulated days (small differences between the scenarios). "Existing" refers to the 2.3 GW of installations.

9.3.3 1 h ramps

Table 27 shows the average number of days per year with at least one ramp event more extreme than the given GW limit for 1 h ramps for those days when the daily max wind speed is above 20 m/s. Comparing to Table 23 (which considers all simulated days) and Table 24 (days when max wind speed is below 20 m/s), it can be seen that proportionally more days with extreme 1 h ramps occur on high wind days (considering that those days are only about 8 % of all simulated days); but this difference is not as clear as with the 5 and 15 min ramps.

Table 27 shows that the Deep type has reduced likelihoods for negative ramps over 2 GW compared to 25 direct cut-off for the 4.0 and 4.4 GW scenarios, but even the Deep type can experience very high negative ramps (3 GW or more), and the Moderate type for BE 4.4 GW Tech B actually shows higher extreme down-ramp than the 25 direct cut-off scenario; this case is visualised in Figure 42. More discussion is provided in Section 9.5. The number of extreme up-ramp events is not significantly reduced when comparing the 25 direct cut-off to the Deep type; this is discussed more in Section 9.4.

Table 27. 1 h ramps: average number of days per year with at least one event more extreme than the limit for days with max fleet-level wind speed above 20 m/s.

		Negative ramp (GW)									Positive ramp (GW)									
		4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	
BE 2018 (877 MW)									1.4	7.3	9.2	2.9								
Existing (2.3 GW)						0.0	0.3	1.7	12.6	20.1	20.5	14.0	2.8	0.6	0.1					
3.0 GW	Tech A	25 m/s				0.0	0.1	0.6	5.0	17.8	22.8	23.3	18.8	6.9	1.8	0.5	0.2			
		Moderate				0.1	0.1	0.6	4.3	15.7	21.7	21.9	17.0	6.4	1.7	0.5	0.2			
		Deep				0.1	0.1	0.5	3.6	15.3	21.6	21.8	16.5	5.3	1.5	0.4	0.1			
	Tech B	25 m/s				0.0	0.1	0.8	4.8	19.1	24.2	24.8	20.3	6.8	1.5	0.4	0.1			
		Moderate				0.0	0.1	0.6	4.5	16.1	22.1	22.7	17.7	6.4	1.5	0.5	0.1			
		Deep				0.1	0.1	0.6	3.8	15.5	22.0	22.4	16.9	5.5	1.4	0.4	0.2			
4.0 GW	Tech A	25 m/s				0.1	1.5	4.8	10.3	19.4	23.4	23.6	20.5	12.2	6.0	2.4	0.7	0.2	0.1	
		Moderate			0.0	0.1	0.8	2.7	7.6	17.1	21.9	22.1	18.1	9.6	4.2	1.6	0.7	0.2	0.1	
		Deep			0.0	0.1	0.3	1.6	6.6	16.6	21.8	21.8	17.9	8.2	3.1	0.8	0.3	0.1	0.1	
	Tech B	25 m/s				0.1	1.4	5.8	12.1	21.3	25.4	25.9	22.0	13.4	6.6	2.2	0.7	0.2	0.1	
		Moderate				0.0	0.1	0.8	3.4	8.0	17.5	23.0	23.8	18.5	9.7	4.0	1.8	0.6	0.3	0.1
		Deep				0.0	0.1	0.3	1.9	6.6	16.9	22.8	23.4	17.8	8.2	2.7	1.1	0.5	0.2	0.1
4.4 GW	Tech A	25 m/s			0.1	1.0	3.4	6.1	12.1	20.7	23.9	24.2	21.5	14.1	7.8	4.0	1.9	0.5	0.2	0.1
		Moderate			0.1	0.3	1.5	3.8	9.1	18.2	22.5	22.7	19.2	11.4	5.5	2.5	1.1	0.5	0.2	0.1
		Deep			0.0	0.2	0.6	2.3	8.2	17.9	22.4	22.5	18.8	10.1	4.1	1.4	0.5	0.2	0.1	0.1
	Tech B	25 m/s			0.1	0.6	4.0	7.6	14.0	22.3	26.4	26.6	23.2	15.4	8.8	4.6	1.6	0.5	0.2	0.1
		Moderate		0.0	0.1	0.3	1.7	4.5	9.6	18.7	24.0	24.5	19.7	11.4	5.5	2.7	1.4	0.5	0.2	0.1
		Deep			0.1	0.2	0.7	2.9	8.2	18.1	23.9	24.4	19.1	9.9	3.9	1.5	0.8	0.4	0.2	0.1

Days with maximum fleet-level wind speed above 20 m/s cover approximately 8 % of the simulated days (small differences between the scenarios). "Existing" refers to the 2.3 GW of installations.

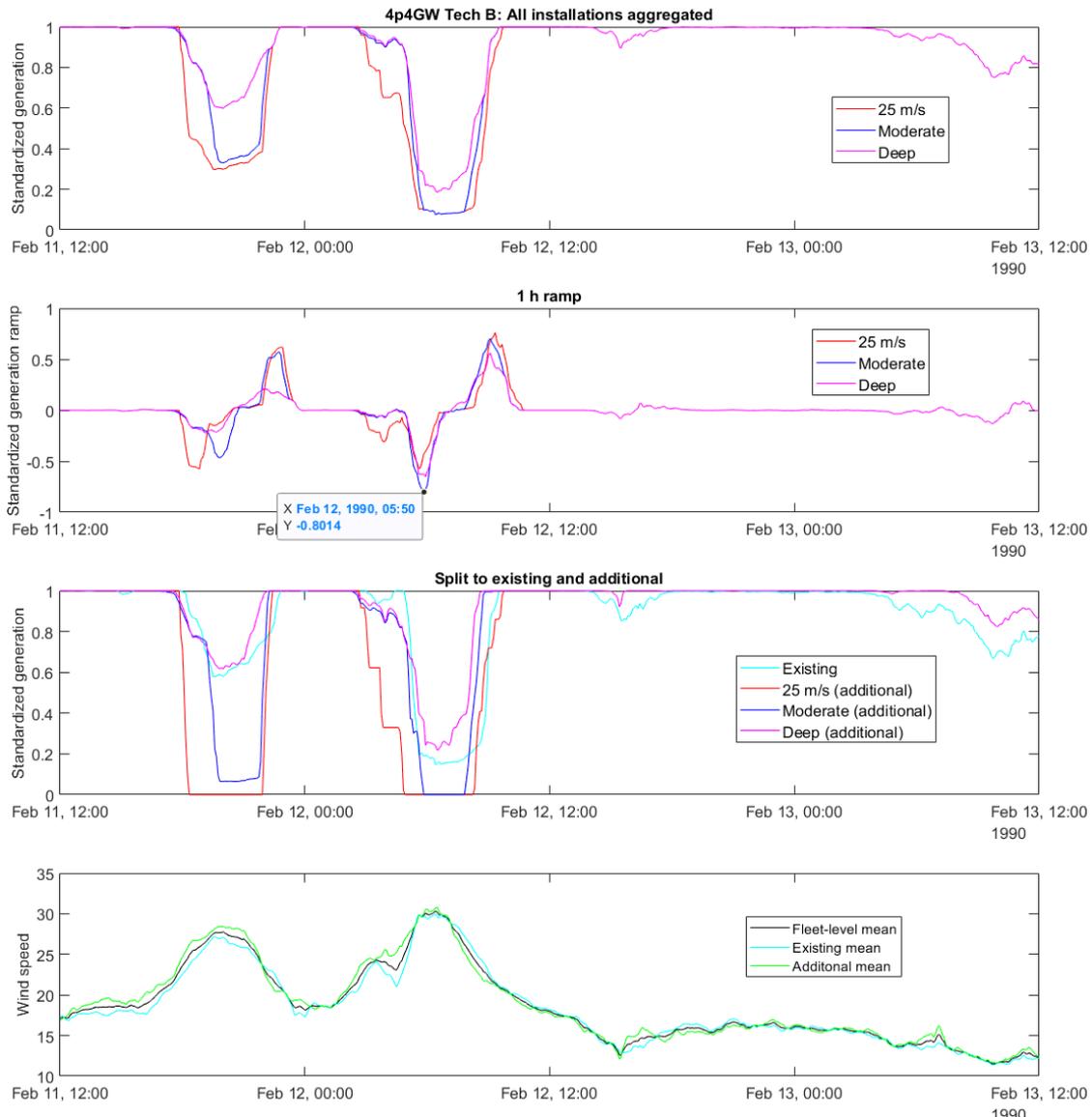


Figure 42. The storm event case for BE 4.4 GW Tech B with more than 3.5 GW 1h down-ramp for the Moderate storm shutdown type. “Existing” refers to the 2.3 GW of installations and “additional” to the 2.1 GW of additional installations to reach 4.4 GW.

9.4 On the large up-ramps

From Table 25, Table 26 and Table 27, it can be seen that up-ramps are more likely than down-ramps of the same magnitude for high wind speed days. For Moderate and Deep types, this is impacted by the storm shutdown types only affecting the shutdown and not the restart operation during storm (this can be seen in Figure 10). An example of this is shown in Figure 43: all the shutdown types experience a very fast 15 min up-ramp. In this case, the Deep and Moderate types show even larger 15 min up-ramp than the 25 direct cut-off type.

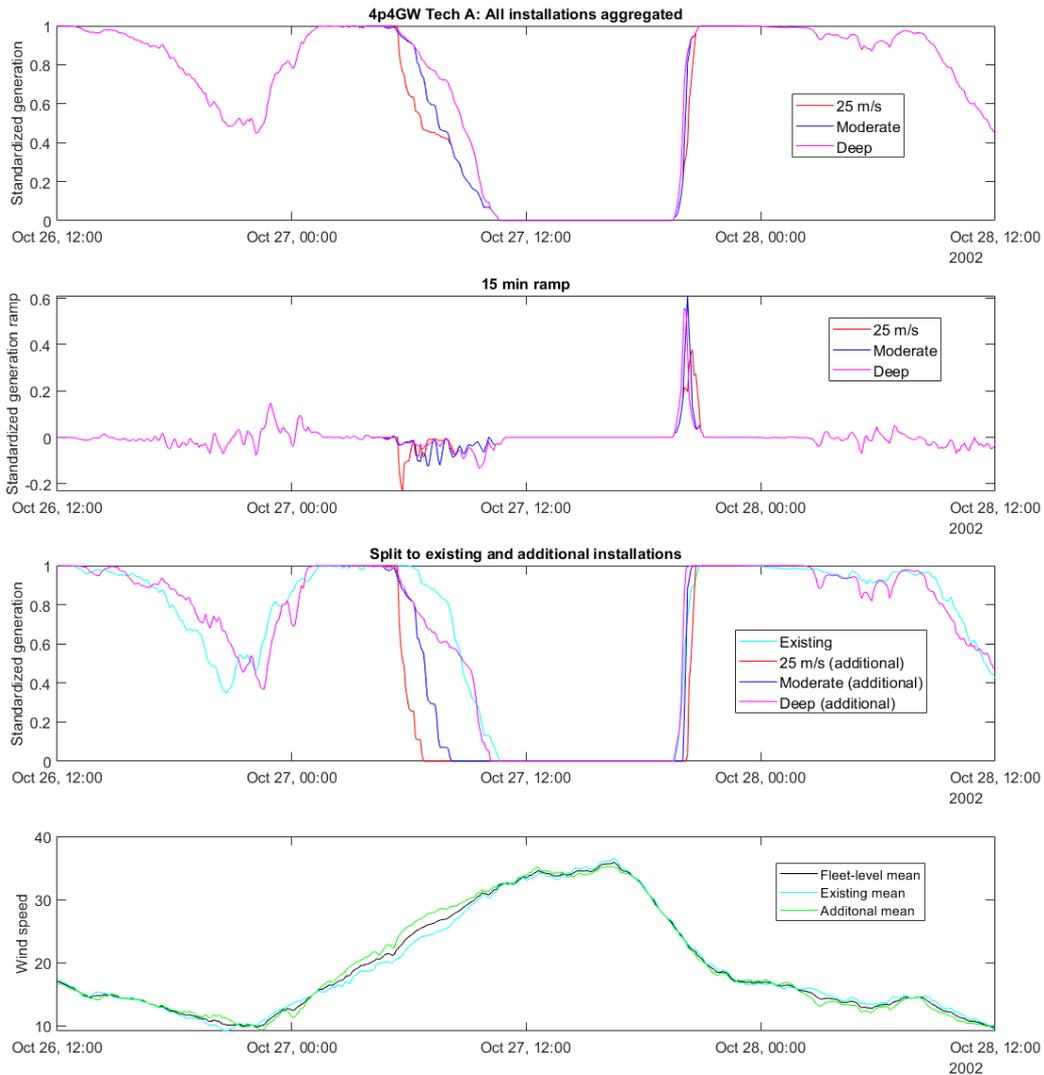


Figure 43. Example storm case for BE 4.4 GW Tech A, where the restart after the storm causes an extreme 15 min up-ramp, especially for the Moderate and the Deep types. “Existing” refers to the 2.3 GW of installations and “additional” to the 2.1 GW of additional installations to reach 4.4 GW.

9.5 On the down-ramps on fleet-level

As was shown in Table 27, the likelihoods of extreme 1 h down-ramp (more than 2.5 GW) during high wind speed day are not very different for the different storm shut-down types, although the 2 GW-level down-ramp likelihoods are reduced compared to moderate and deep types (considering the 4.4 GW scenarios). A very clear reason for this was not found; however, it seems that during the extreme ramps cases there can be an unfortunate correlation of ramps between the 2.3 GW and additional installations. An example of this can be seen in Figure 44: when looking only at the additional installations (3rd subplot), the Deep type shows smoother storm operation compared to the 25 direct cut-off. However, it can be seen in the same subplot that the storm shut-down of the additional Deep type correlates with the shut-down operation of the 2.3 GW of installations. As a result, on the aggregate 4.4 GW-level, the 1 h ramp of the Deep scenario is more severe than the 25 direct cut-off scenario. This unfortunate lag (additional installations ramping down first and the 2.3 GW later) is related to the wind speed in the additional installations increasing before the wind speeds in the 2.3 GW locations increase (bottom subplot of Figure 44).

Similar phenomena as in Figure 44 can be seen also in Figure 42; in Figure 42, the Moderate type shows the most severe 1 h down-ramp.

The above-mentioned phenomena may relate to storms usually coming from the west (see Figure 7 on the geographical locations of the installations); this would explain the wind speeds increasing first in the additional 2.1 GW (west) installations and later in the 2.3 GW installations (east). A geographical visualisation in Figure 45 of the time series in Figure 44 seems to show that at least in this case the storm moved from west to east. However, the reasons behind these observations have not been fully assessed and would need a deeper analysis before being confirmed. The phenomena was seen on 1 h ramps, but not so significantly on the 5 min or 15 min ramps, which might be explained by the distance between the 2.3 GW and the additional 2.1 GW installation clusters.

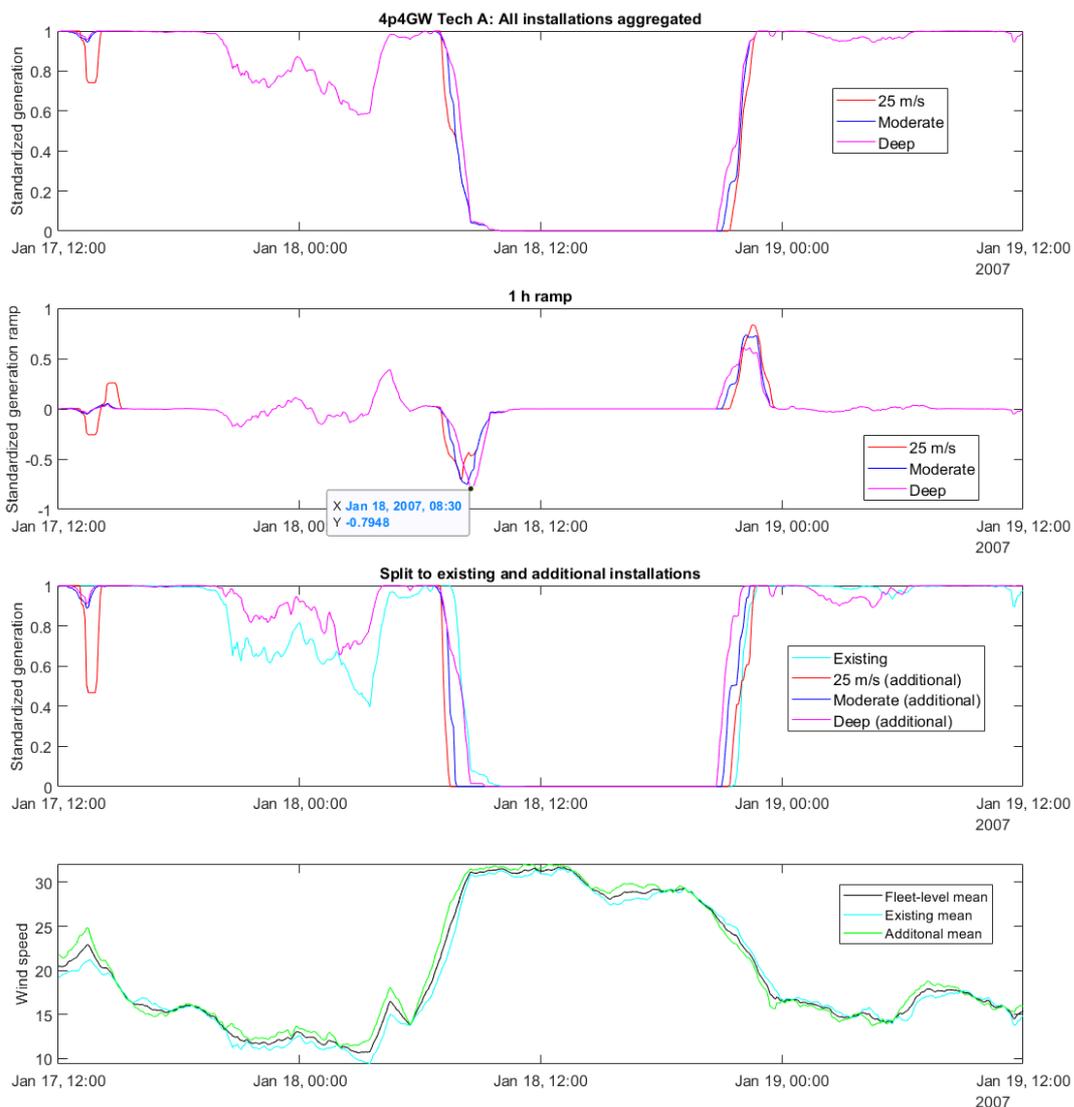


Figure 44. Example storm case for BE 4.4 GW Tech A, where largest 1 h down-ramp for the Deep type is more severe than for the 25 direct cut-off. “Existing” refers to the 2.3 GW of installations and “additional” to the 2.1 GW of additional installations to reach 4.4 GW.

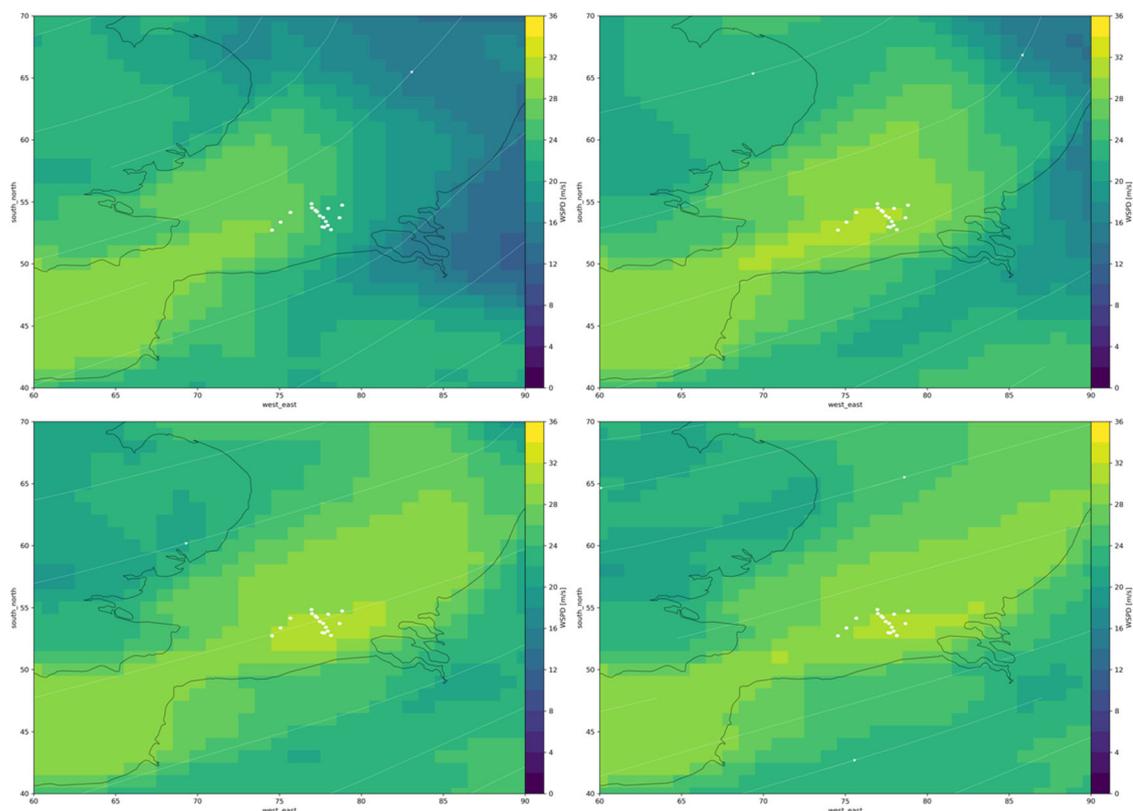


Figure 45. Wind speed maps (WRF directly) and wind direction streamlines for the example storm case for BE 4.4 GW Tech A, where largest 1 h down-ramp for the Deep type is more severe than for the 25 direct cut-off. Top left: 18 January 2007 07:00 AM. Top right: 18 January 2007 8:00 AM. Bottom left: 18 January 2007 9:00 AM. Bottom right: 18 January 2007 10:00 AM.

9.6 Conclusions on storm events

It is possible to lose the full 4.4 GW of installed capacity in all studied cases due to an extreme storm event. The number of years where this occurs is 6 or 7 out of the simulated 37 years for the 4.4 GW scenarios, depending on the technology scenario.

Storm shutdown type impacts the most extreme fast ramps by slowing down the down-ramps during storms. 5 and 15 min extreme down ramps are reduced significantly when comparing the Deep to the 25 direct cut-off type. The following numbers are for the 4.4 GW scenarios. For 15 min ramps, a larger than 2 GW down-ramp was seen in the simulations a few times over the 37 years for the 25 direct cut-off types, but such event was not seen for scenarios with the Deep or Moderate storm type. The Deep type shows a reduction of down-ramps compared to the Moderate type: 15 min down-ramps of > 1 GW and > 1.5 GW are approximately half as likely for the Deep than for the Moderate type. A 5 min down-ramp of more than 1 GW is expected less than once a year for the 25 direct cut-off type, but such event is not seen for scenarios with the Deep type, and only once in the simulated 37 years for the Moderate type. A 5 min down-ramp of more than 0.5 GW is expected to occur on multiple days a year for the 25 direct cut-off type, on 1 or 2 days for the Moderate type and less than one day a year for the Deep type.

For 1 hour ramps in the 4.4 GW scenarios on high wind speed days, a down-ramp event of more than 2 GW is expected to happen on a few days over a year with the 25 direct cut-off type. For similar scenarios with the Deep storm shutdown type, such event is expected on less than one day a year. However, on the fleet-level (4 or 4.4 GW), the most severe 1 hour down-ramps are similar for all shutdown types. A very clear reason was not found, but it may be because of storms coming from the west and causing shut-down first for the additional 2.1 GW installations and after some time for the 2.3 GW installations, which can cause an unfortunate aggregate down-ramp event on the fleet-level (see Section 9.5).

Highest 1 h up-ramps (restarts) are similar for all studied storm shutdown types. A contributor to this is that the storm shut-down slows only the shut-down and not the restart part of the power curve. However, it needs to be noted that a smoother restart operation would not remove all extreme up-ramps, as they can happen even on low wind days (see Section 8.4).

10. Statistical analysis of forecast errors

This chapter analyses the simulated forecast errors for the scenarios. The forecast errors are calculated as: $e_t = p_{t,actual} - p_{t,forecasted}$. Thus, a negative forecast error means that forecasted is larger than actual generation. All forecast errors are analysed on 15 min resolution.

The first section compares the scenarios in standardized generation, as the impact of geographical smoothening is easier to see when all data are standardized. The further sections show results mostly in GW.

10.1 Results in standardized generation

10.1.1 Day-ahead forecasts

Table 28 shows the day-ahead forecast error statistics for the different scenarios. It can be seen that the forecast error SD decreases from the BE 2018 scenario towards the 4.4 GW scenarios. This decrease is due to increased geographical distribution (on aggregate, it is easier to forecast a larger than a smaller region). Tech A and Tech B scenarios show similar statistics. The Deep storm shut-down type shows very slightly reduced likelihoods for very large forecast errors compared to 25 direct cut-off.

Table 28. Day-head forecast error statistics.

							Compared to BE 2018		
			mean	SD	Prct 0.001	Prct 0.01	Prct 99.99	Prct 99.999	SD
BE 2018 (877 MW)			-0.002	0.134	-0.952	-0.747	0.741	0.971	100%
2.3 GW			-0.001	0.127	-0.791	-0.691	0.648	0.727	95%
3.0 GW	Tech A	25 m/s	-0.001	0.122	-0.731	-0.641	0.616	0.732	91%
		Moderate	-0.002	0.121	-0.739	-0.646	0.608	0.682	90%
		Deep	-0.002	0.121	-0.731	-0.639	0.607	0.682	90%
	Tech B	25 m/s	-0.001	0.121	-0.710	-0.637	0.606	0.698	90%
		Moderate	-0.001	0.121	-0.710	-0.637	0.601	0.679	90%
		Deep	-0.001	0.120	-0.710	-0.642	0.598	0.678	90%
4.0 GW	Tech A	25 m/s	-0.001	0.116	-0.702	-0.617	0.589	0.759	87%
		Moderate	-0.001	0.115	-0.721	-0.616	0.578	0.673	86%
		Deep	-0.001	0.115	-0.695	-0.607	0.570	0.673	86%
	Tech B	25 m/s	-0.001	0.116	-0.681	-0.605	0.576	0.712	87%
		Moderate	-0.001	0.115	-0.682	-0.610	0.570	0.681	86%
		Deep	-0.001	0.114	-0.681	-0.605	0.566	0.670	85%
4.4 GW	Tech A	25 m/s	-0.001	0.116	-0.700	-0.618	0.601	0.775	87%
		Moderate	-0.001	0.115	-0.710	-0.618	0.581	0.680	86%
		Deep	-0.001	0.115	-0.688	-0.604	0.571	0.671	85%
	Tech B	25 m/s	-0.001	0.117	-0.697	-0.610	0.584	0.728	87%
		Moderate	-0.001	0.115	-0.694	-0.617	0.576	0.682	86%
		Deep	-0.001	0.114	-0.677	-0.605	0.569	0.673	85%

10.1.2 Intraday forecasts

Table 29 shows the intraday forecast error statistics. It can be seen that the forecast error SD decreases from the BE 2018 scenario towards the 4.4 GW scenarios. Tech A and Tech B scenarios show similar statistics. The forecast error SDs are somewhat lower than for day-ahead (Table 28). The different storm shut-down types show similar forecast error statistics.

Table 29. Intraday forecast error statistics.

							Compare d to BE 2018		
			mean	SD	Prct 0.001	Prct 0.01	Prct 99.99	Prct 99.999	SD
BE 2018 (877 MW)			0.000	0.111	-0.840	-0.615	0.661	0.847	100%
2.3 GW			-0.001	0.107	-0.684	-0.584	0.559	0.666	96%
3.0 GW	Tech A	25 m/s	-0.001	0.102	-0.636	-0.551	0.525	0.607	91%
		Moderate	-0.001	0.102	-0.639	-0.553	0.525	0.608	91%
		Deep	-0.001	0.101	-0.639	-0.553	0.525	0.607	91%
	Tech B	25 m/s	-0.001	0.102	-0.611	-0.543	0.523	0.606	91%
		Moderate	-0.001	0.101	-0.614	-0.546	0.526	0.606	91%
		Deep	-0.001	0.101	-0.616	-0.548	0.525	0.606	91%
4.0 GW	Tech A	25 m/s	-0.001	0.097	-0.623	-0.539	0.511	0.607	87%
		Moderate	-0.001	0.096	-0.611	-0.530	0.503	0.602	87%
		Deep	-0.001	0.096	-0.607	-0.524	0.493	0.561	86%
	Tech B	25 m/s	0.000	0.097	-0.607	-0.524	0.511	0.589	87%
		Moderate	0.000	0.096	-0.626	-0.523	0.508	0.599	86%
		Deep	0.000	0.096	-0.602	-0.517	0.494	0.559	86%
4.4 GW	Tech A	25 m/s	0.000	0.097	-0.643	-0.549	0.529	0.638	87%
		Moderate	-0.001	0.096	-0.620	-0.538	0.505	0.602	86%
		Deep	-0.001	0.096	-0.614	-0.523	0.495	0.563	86%
	Tech B	25 m/s	0.000	0.098	-0.615	-0.539	0.523	0.621	88%
		Moderate	0.000	0.096	-0.641	-0.535	0.514	0.622	87%
		Deep	0.000	0.096	-0.613	-0.522	0.495	0.562	86%

10.1.3 Latest forecasts

Table 30 shows the “Last” forecast error statistics for the scenarios. It can be seen that the forecast error SD decreases from the BE 2018 scenario towards the 4.4 GW scenarios; the reduction is slightly larger than for the day-ahead and intraday forecast errors. Tech A and Tech B scenarios show similar statistics. The Deep storm shut-down type shows slightly reduced likelihoods for very large forecast errors compared to 25 direct cut-off.

Table 30. “Last” forecast error statistics.

							Compared to BE 2018		
			mean	SD	Prct 0.001	Prct 0.01	Prct 99.99	Prct 99.999	SD
BE 2018 (877 MW)			0.001	0.072	-0.669	-0.490	0.554	0.726	100%
2.3 GW			0.009	0.071	-0.587	-0.429	0.490	0.650	98%
3.0 GW	Tech A	25 m/s	0.008	0.064	-0.538	-0.388	0.442	0.608	88%
		Moderate	0.008	0.063	-0.519	-0.389	0.441	0.576	88%
		Deep	0.008	0.063	-0.524	-0.382	0.436	0.577	87%
	Tech B	25 m/s	0.010	0.064	-0.541	-0.388	0.432	0.597	88%
		Moderate	0.010	0.063	-0.519	-0.386	0.432	0.572	88%
		Deep	0.010	0.063	-0.528	-0.382	0.428	0.579	87%
4.0 GW	Tech A	25 m/s	0.007	0.057	-0.516	-0.417	0.414	0.556	79%
		Moderate	0.007	0.056	-0.488	-0.365	0.395	0.537	78%
		Deep	0.007	0.056	-0.473	-0.342	0.376	0.535	77%
	Tech B	25 m/s	0.011	0.058	-0.529	-0.414	0.411	0.572	80%
		Moderate	0.011	0.057	-0.494	-0.369	0.410	0.543	79%
		Deep	0.012	0.057	-0.485	-0.338	0.390	0.523	78%
4.4 GW	Tech A	25 m/s	0.006	0.057	-0.548	-0.450	0.419	0.569	79%
		Moderate	0.007	0.056	-0.497	-0.374	0.398	0.539	77%
		Deep	0.007	0.056	-0.473	-0.342	0.376	0.539	77%
	Tech B	25 m/s	0.011	0.058	-0.554	-0.450	0.424	0.587	80%
		Moderate	0.012	0.057	-0.505	-0.381	0.413	0.547	79%
		Deep	0.012	0.057	-0.480	-0.343	0.393	0.524	78%

10.2.2 Intraday forecasts

Table 32 shows the average number of days per year with at least one intraday forecast error more extreme than the given GW limit. Tech A and Tech B show similar statistics; the most extreme forecast errors are marginally less likely for the Deep storm shutdown type compared to 25 direct cut-off.

Table 32. Intraday forecast errors: average number of days per year with at least one event.

		Negative forecast error (GW)								Positive forecast error (GW)										
		4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	
Existing (2.3 GW)							0.6	15.6	152.0	253.3	255.6	152.4	12.2	0.3						
3.0 GW	Tech A	25 m/s					0.0	3.5	40.9	201.4	281.6	283.7	202.9	37.2	2.2	0.0				
		Moderate					0.1	3.5	40.5	199.3	280.1	282.2	200.7	36.8	2.3	0.1				
		Deep					0.1	3.5	40.3	198.9	279.9	282.0	200.3	36.2	2.2	0.0				
	Tech B	25 m/s						3.2	39.6	203.1	284.6	285.9	202.8	35.5	1.9	0.0				
		Moderate						0.0	3.1	39.6	200.5	282.6	283.7	200.5	35.5	1.9	0.0			
		Deep						0.0	3.2	39.3	200.0	282.2	283.4	199.8	34.9	1.9	0.0			
4.0 GW	Tech A	25 m/s				0.1	2.4	17.8	86.2	243.3	304.2	303.1	241.5	81.6	15.2	1.8	0.1			
		Moderate					0.1	2.1	16.8	84.3	240.9	302.4	301.5	239.1	79.8	13.8	1.5	0.1		
		Deep					0.1	2.0	16.4	83.6	240.5	302.1	301.4	238.6	78.6	13.2	1.3			
	Tech B	25 m/s					0.1	2.3	18.1	87.5	246.9	307.6	305.4	243.8	81.7	15.2	1.5	0.1		
		Moderate					0.1	2.1	16.7	84.8	243.4	304.8	303.4	240.7	79.5	13.8	1.4	0.1		
		Deep					0.1	2.0	16.2	83.7	242.6	304.5	303.0	239.7	78.2	13.1	1.1	0.1		
4.4 GW	Tech A	25 m/s			0.0	0.9	5.7	28.8	111.3	258.8	311.4	310.6	257.0	105.0	24.9	4.2	0.5	0.1		
		Moderate			0.0	0.7	4.9	27.3	108.7	256.3	309.5	309.2	254.7	102.9	23.1	2.9	0.4	0.1		
		Deep			0.0	0.6	4.7	26.7	108.1	256.0	309.2	309.0	254.3	101.7	22.2	2.7	0.2			
	Tech B	25 m/s			0.0	0.8	6.1	30.4	113.4	261.1	314.4	312.3	258.4	105.7	25.5	4.6	0.3	0.0		
		Moderate			0.1	0.5	5.0	28.1	110.1	257.5	311.7	310.3	255.3	102.9	23.6	3.5	0.4	0.0		
		Deep			0.0	0.5	4.7	27.5	108.9	256.8	311.3	310.2	254.6	101.6	22.6	2.9	0.2			

“Existing” refers to the 2.3 GW of installations.

10.2.3 Latest forecasts

Table 33 shows the average number of days per year with at least one “Last” forecast error more extreme than the given GW limit. Tech A and Tech B show similar statistics; the most extreme forecast errors are slightly less likely for the Deep storm shutdown type compared to 25 direct cut-off.

Table 33. “Last” forecast errors: average number of days per year with at least one event.

		Negative forecast error (GW)								Positive forecast error (GW)												
		4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0			
Existing (2.3 GW)							0.1	1.8	80.3	231.1	265.1	125.4	4.1	0.2								
3.0 GW	Tech A	25 m/s					0.0	0.2	6.3	128.6	268.5	290.7	179.8	11.1	0.5	0.1						
		Moderate					0.0	0.3	6.1	125.8	266.6	289.3	178.4	10.7	0.5	0.1						
		Deep					0.0	0.3	5.6	124.8	266.3	289.0	178.1	10.4	0.5	0.0						
	Tech B	25 m/s					0.0	0.3	5.7	119.9	264.0	298.5	189.1	11.0	0.6	0.1						
		Moderate					0.1	0.3	5.6	116.1	260.4	296.6	187.5	10.8	0.6	0.1						
		Deep					0.1	0.3	5.2	114.8	260.1	296.2	187.2	10.5	0.6	0.0						
4.0 GW	Tech A	25 m/s			0.0	0.3	3.6	20.2	182.9	295.0	309.7	227.8	28.5	3.1	0.5	0.1						
		Moderate			0.0	0.2	1.5	17.1	179.4	292.6	307.9	225.6	27.2	2.4	0.4	0.1	0.0					
		Deep				0.2	0.9	15.4	178.5	292.3	307.7	225.2	26.1	1.8	0.3	0.1						
	Tech B	25 m/s			0.0	0.3	3.8	18.9	161.7	286.9	320.6	251.4	36.0	3.1	0.4	0.1	0.0					
		Moderate			0.0	0.2	1.8	14.6	156.3	282.8	318.4	248.5	33.9	2.6	0.4	0.1	0.0					
		Deep				0.2	1.0	12.7	155.1	282.2	317.9	248.0	32.9	2.2	0.2	0.1	0.0					
4.4 GW	Tech A	25 m/s			0.0	0.1	1.8	5.9	29.8	212.1	305.7	317.4	248.8	45.2	5.4	1.1	0.2	0.0				
		Moderate				0.0	0.4	3.5	26.2	208.4	303.3	315.6	246.3	43.1	4.4	0.7	0.1	0.1				
		Deep				0.2	2.3	24.4	207.7	303.1	315.4	246.0	42.0	3.6	0.4	0.1	0.0					
	Tech B	25 m/s			0.2	1.5	6.4	28.0	189.9	298.8	327.5	273.9	59.4	6.6	1.2	0.2	0.1					
		Moderate			0.0	0.1	0.4	3.5	22.5	184.4	294.9	325.5	270.6	56.4	5.5	0.9	0.1	0.1				
		Deep			0.1	0.3	2.0	20.4	183.2	294.4	325.1	270.0	55.2	4.9	0.6	0.1	0.0					

“Existing” refers to the 2.3 GW of installations-

10.3 Forecast errors during high and low wind speed days

Table 34 and Table 35 show the average number of days per year with at least one day-ahead forecast error more extreme than the given GW limit with split to high and low wind speed days, respectively. Tech A and Tech B show similar statistics in both tables. For high wind speed days, the Deep type show slightly lower likelihoods for very high forecast errors compared to 25 direct cut-off. Proportionally, the high wind speed days show more extreme forecast errors (considering that they present only ~8% of the simulated days).

Similar tables are given for intraday:

- Appendix H: Intraday forecast errors for days with maximum wind speed above 20 m/s
- Appendix I: Intraday forecast errors for days with maximum wind speed below 20 m/s.

And for “Last”:

- Appendix J: Latest forecast errors for days with maximum wind speed above 20 m/s
- Appendix K: Latest forecast errors for days with maximum wind speed below 20 m/s.

Table 34. Day-ahead forecast errors: average number of days per year with at least one event when the daily max fleet-level wind speed is above 20 m/s.

		Negative forecast error (GW)										Positive forecast error (GW)									
		4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0		
Existing (2.3 GW)							0.1	1.0	8.2	14.3	13.3	7.6	1.2	0.2							
3.0 GW	Tech A	25 m/s					0.1	0.5	3.7	12.7	17.6	17.0	12.2	3.7	0.6	0.1					
		Moderate					0.1	0.5	2.9	11.0	16.2	15.4	10.1	3.0	0.5	0.0					
		Deep					0.1	0.4	2.7	10.6	16.1	15.3	9.9	2.6	0.4	0.0					
	Tech B	25 m/s					0.0	0.4	3.1	13.9	18.6	18.1	13.0	3.6	0.5	0.1					
		Moderate					0.0	0.4	2.8	11.5	16.8	16.3	10.6	3.1	0.4	0.1					
		Deep					0.1	0.4	2.5	10.9	16.5	15.9	9.9	2.5	0.4	0.0					
4.0 GW	Tech A	25 m/s			0.0	0.2	1.0	3.0	6.9	14.8	19.0	18.7	14.8	7.4	3.2	1.1	0.1	0.1			
		Moderate			0.0	0.1	0.5	1.8	5.1	12.6	17.0	16.7	12.3	5.1	1.6	0.5	0.1	0.0			
		Deep				0.0	0.3	1.4	4.5	12.2	16.8	16.5	11.8	4.2	1.2	0.2	0.0	0.0			
	Tech B	25 m/s			0.0	0.1	0.8	3.2	7.5	16.4	20.9	20.4	15.9	7.9	3.8	1.1	0.1	0.1			
		Moderate				0.1	0.6	1.9	5.2	13.2	18.1	18.1	12.8	5.4	1.9	0.5	0.1	0.0			
		Deep				0.1	0.4	1.3	4.4	12.4	17.8	17.6	11.9	4.0	1.2	0.2	0.1	0.0			
4.4 GW	Tech A	25 m/s			0.1	0.6	1.9	4.0	8.5	15.8	19.5	19.3	15.8	8.4	4.3	2.2	0.6	0.1	0.1		
		Moderate			0.1	0.4	0.8	2.4	6.2	13.4	17.8	17.5	13.2	5.8	2.2	0.8	0.3	0.1	0.0		
		Deep				0.1	0.5	2.0	5.6	12.9	17.6	17.3	12.9	4.8	1.6	0.5	0.1	0.0	0.0		
	Tech B	25 m/s			0.1	0.5	2.0	4.8	9.5	17.6	21.8	21.2	16.8	9.3	4.8	2.8	0.5	0.1	0.0		
		Moderate			0.1	0.3	1.0	2.8	6.3	14.2	19.0	18.9	13.7	6.4	2.6	0.9	0.3	0.1	0.0		
		Deep			0.0	0.2	0.5	1.9	5.4	13.5	18.7	18.5	13.1	5.1	1.5	0.4	0.1	0.0	0.0		

15 min resolution data. Days with maximum fleet-level wind speed above 20 m/s cover approximately 8 % of the simulated days. “Existing” refers to the 2.3 GW of installations.

Table 35. Day-ahead forecast errors: average number of days per year with at least one event when the daily max fleet-level wind speed is below 20 m/s.

		Negative forecast error (GW)										Positive forecast error (GW)									
		4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0		
Existing (2.3 GW)							1.3	21.5	130.8	207.4	208.5	130.9	19.5	0.8							
3.0 GW	Tech A	25 m/s					0.6	6.6	46.8	163.7	230.6	230.6	163.2	43.8	5.3	0.2					
		Moderate					0.6	6.6	46.8	163.6	230.6	230.5	163.1	43.8	5.3	0.2					
		Deep					0.6	6.6	46.8	163.6	230.6	230.5	163.1	43.8	5.3	0.2					
	Tech B	25 m/s					0.4	6.2	46.2	164.7	231.3	230.7	162.2	42.9	4.9	0.2					
		Moderate					0.4	6.2	46.2	164.6	231.3	230.6	162.1	42.8	4.9	0.2					
		Deep					0.4	6.2	46.2	164.6	231.3	230.6	162.1	42.8	4.9	0.2					
4.0 GW	Tech A	25 m/s				0.6	4.2	22.9	82.6	196.2	251.5	250.0	194.0	77.5	20.1	3.5	0.2				
		Moderate				0.6	4.2	22.9	82.6	196.2	251.5	249.9	193.9	77.4	20.1	3.5	0.2				
		Deep				0.6	4.2	22.9	82.6	196.2	251.5	249.9	193.9	77.5	20.1	3.5	0.2				
	Tech B	25 m/s			0.0	0.5	4.5	23.1	82.1	198.2	252.9	249.1	193.4	76.4	19.8	3.1	0.2				
		Moderate			0.0	0.5	4.5	23.1	82.1	198.2	252.8	248.9	193.2	76.4	19.8	3.1	0.2				
		Deep			0.0	0.5	4.5	23.1	82.1	198.2	252.8	248.9	193.2	76.4	19.8	3.1	0.2				
4.4 GW	Tech A	25 m/s			0.2	1.4	8.5	33.9	99.4	208.6	259.2	258.4	206.2	93.4	30.3	6.3	0.8	0.0			
		Moderate			0.2	1.4	8.5	33.9	99.4	208.6	259.2	258.3	206.1	93.4	30.3	6.3	0.8	0.0			
		Deep			0.2	1.4	8.5	33.9	99.4	208.6	259.2	258.3	206.1	93.4	30.3	6.3	0.8	0.0			
	Tech B	25 m/s			0.1	1.5	9.1	35.4	99.5	209.8	259.9	255.6	205.9	93.2	30.3	6.5	0.9	0.0			
		Moderate			0.1	1.5	9.1	35.4	99.5	209.7	259.9	255.4	205.7	93.2	30.3	6.5	0.9	0.0			
		Deep			0.1	1.5	9.1	35.4	99.5	209.7	259.9	255.4	205.7	93.2	30.3	6.5	0.9	0.0			

15 min resolution data. Days with maximum fleet-level wind speed below 20 m/s cover approximately 92 % of the simulated days. “Existing” refers to the 2.3 GW of installations.

10.4 Forecast errors during high ramp and storm days

10.4.1 High ramp and storm days

High ramp days are defined as days with a maximum ramp > 2 GW (either negative or positive ramp); the most extreme of the 5 min, 15 min and 1 h ramp defines the maximum ramp of the day. These days are listed for the simulations and provided to Elia (see Section 12).

For the purpose of this analysis, storm days are defined as high ramp days where max wind speed of the day is above 20 m/s and where the extreme ramp (> 2 GW) happens during the time when wind speed is above 20 m/s (this is done by identifying the first and last time step of the day when wind speed is > 20 m/s; if for a while wind speed drops below 20 m/s, it is still considered part of storm event). The storm days are also listed and provided to Elia (see Section 12).

Average days per year of the high ramp and storm days are given in Table 36. For the BE 4.0 and BE 4.4 GW scenarios, where the additional installations constitute a significant share of the total fleet, the Deep type shows significantly less storm days with high ramp compared to the 25 direct cut-off shutdown type; even though wind speeds are the same for both storm shut-down types, the Deep type experiences less days with high ramp. This is in line with Table 27: the likelihood of higher than 2 GW ramp is reduced for Deep compared to 25 direct cut-off. In Table 36, Tech B shows some increase in the average number of days per year compared to Tech A.

Table 36. Average number of high ramp and storm days per year.

			Average number of days per year	
			High ramp days	Storm days with high ramp
3.0 GW	Tech A	25 m/s	1.2	0.3
		Moderate	1.3	0.4
		Deep	1.2	0.3
	Tech B	25 m/s	1.2	0.3
		Moderate	1.3	0.3
		Deep	1.2	0.3
4.0 GW	Tech A	25 m/s	7.1	2.8
		Moderate	5.8	1.5
		Deep	4.8	0.5
	Tech B	25 m/s	7.0	2.6
		Moderate	6.1	1.7
		Deep	5.1	0.7
4.4 GW	Tech A	25 m/s	12.7	4.5
		Moderate	10.4	2.1
		Deep	8.9	0.6
	Tech B	25 m/s	13.8	5.5
		Moderate	10.7	2.5
		Deep	9.1	0.8

10.4.2 Daily extreme forecast errors during high ramp days

Figure 46 shows the distributions of min and max forecast errors of the day for all simulated days, and for high ramp days (ramp > 2 GW) for BE 4.4 GW Tech A. It can be seen that for all forecast horizons, the high ramp days show increased likelihood for high forecast error. For the “Last” horizon, this impact is very significant.

In Figure 46, the distributions of min and max errors of all days for “Last” are more skewed than for day-ahead and intraday: this indicates that while on average “Last” shows lower forecast errors than DA or intraday (Table 30 vs. Table 28 and Table 29), there are some days when the “Last” forecasts show high errors. The distributions of the daily min and max forecast errors on high ramp days indicate that those large forecast errors are more likely to happen during high ramp days.

Table 37 shows that high (> 40 % of installed capacity) negative and positive DA forecast errors are more likely during high ramp days. The Deep type shows significantly lower forecast errors during high ramp days compared to 25 direct cut-off.

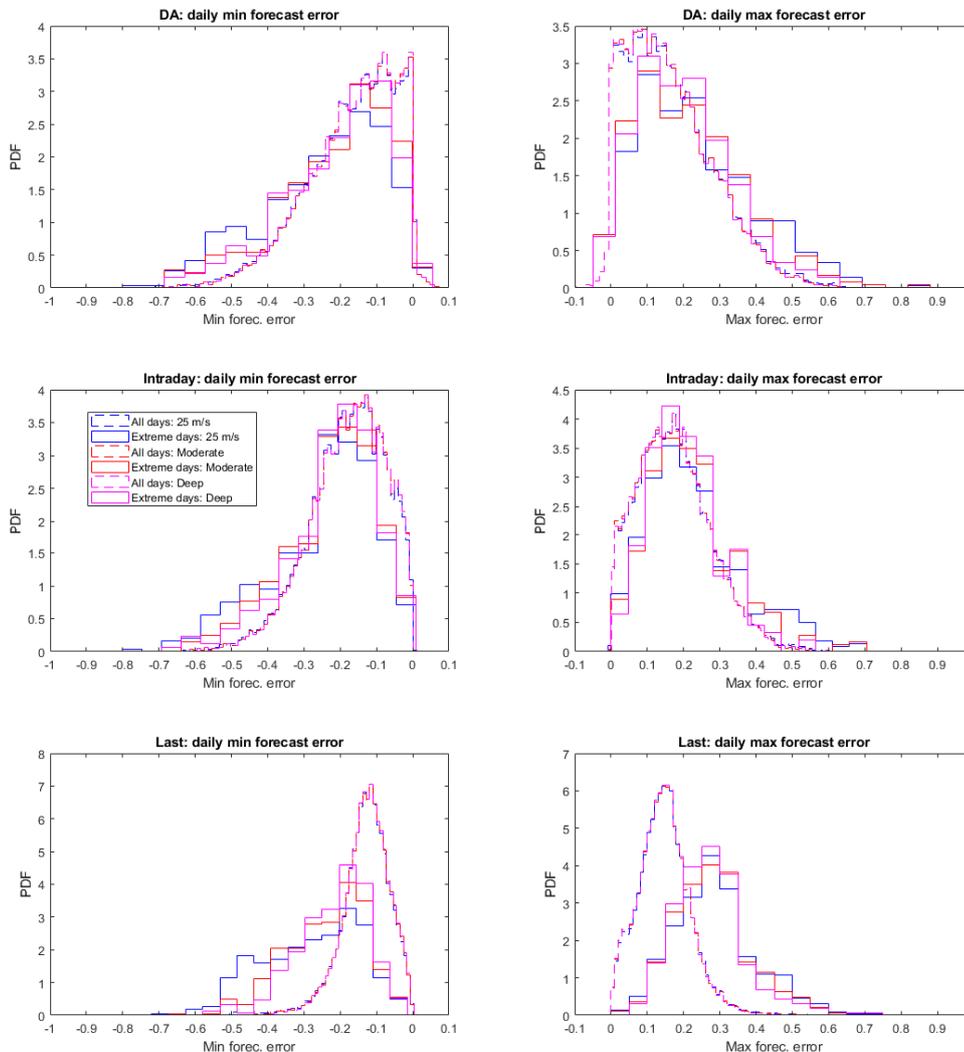


Figure 46. Distributions of max and mix forecast error of the day for all simulated days and for high ramp days (noted “extreme days” in the figure) for BE 4.4 GW Tech A.

Table 37. Share of days with maximum day-ahead forecast error below -0.4 or above 0.4 in standardized generation; comparison of all days and high ramp days.

			Number of days		Share of days with forec. err. < -0.4		Share of days with forec. err. > 0.4	
			All days	High ramp days	All days	High ramp days	All days	High ramp days
4.0 GW	Tech A	25 m/s	13514	262	5%	18%	5%	16%
		Moderate	13514	216	5%	13%	4%	12%
		Deep	13514	179	5%	12%	4%	7%
	Tech B	25 m/s	13514	259	5%	14%	5%	15%
		Moderate	13514	225	5%	13%	4%	12%
		Deep	13514	189	5%	12%	4%	8%
4.4 GW	Tech A	25 m/s	13513	469	5%	19%	5%	15%
		Moderate	13513	383	5%	12%	4%	11%
		Deep	13513	328	5%	11%	4%	8%
	Tech B	25 m/s	13513	511	6%	19%	5%	16%
		Moderate	13513	396	5%	15%	4%	11%
		Deep	13513	336	5%	13%	4%	8%

10.4.3 Daily extreme forecast errors during storm days

Figure 47 shows the distributions of min and max forecast errors of the day for all simulated days and for storm days for BE 4.4 GW Tech A. It can be seen that for all forecast horizons, the storm days show significantly increased likelihood for high forecast error; however, the estimation of forecast error distributions for storm days is challenging due to small number of days falling into the storm definition (see Section 10.4.1), as can be seen in Table 36. An example of a storm case with large DA forecast error can be seen in Figure 48; there is significant forecast error both during the shut-down and the restart part of the event.

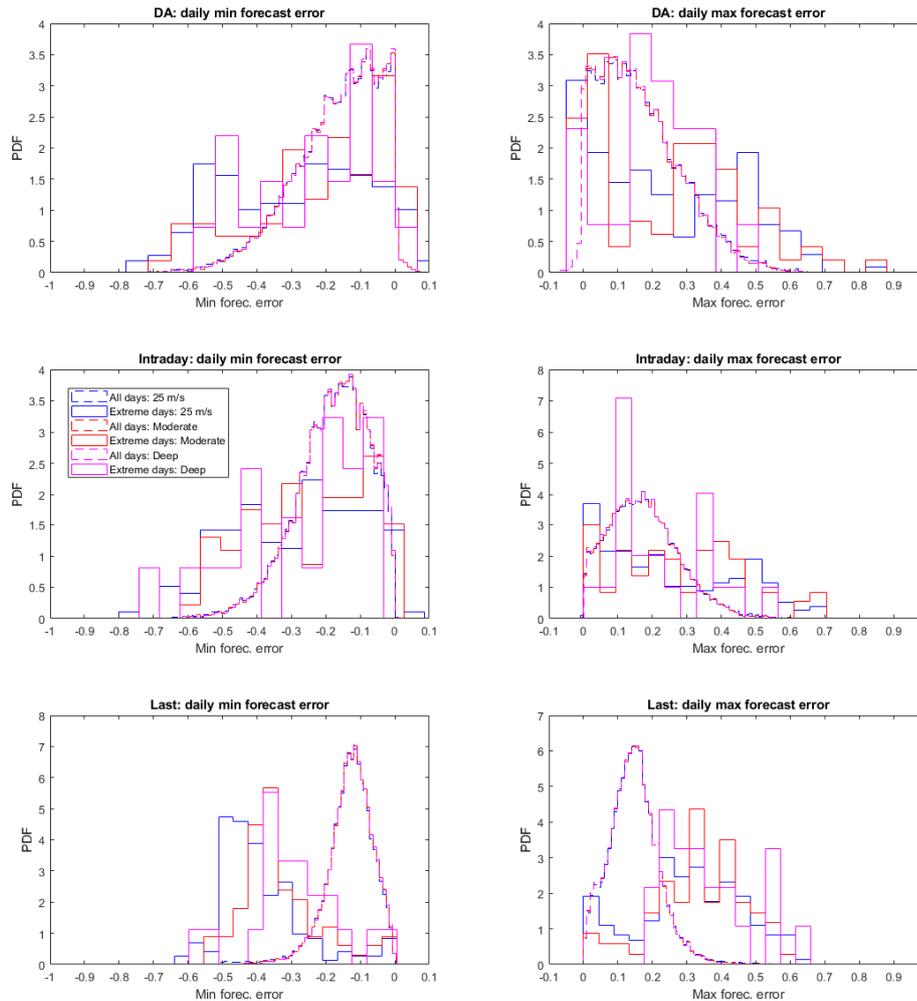


Figure 47. Distributions of max and mix forecast error of the day for all simulated days and for storm days with high ramp (noted “extreme days” in the figure) for BE 4.4 GW Tech A.

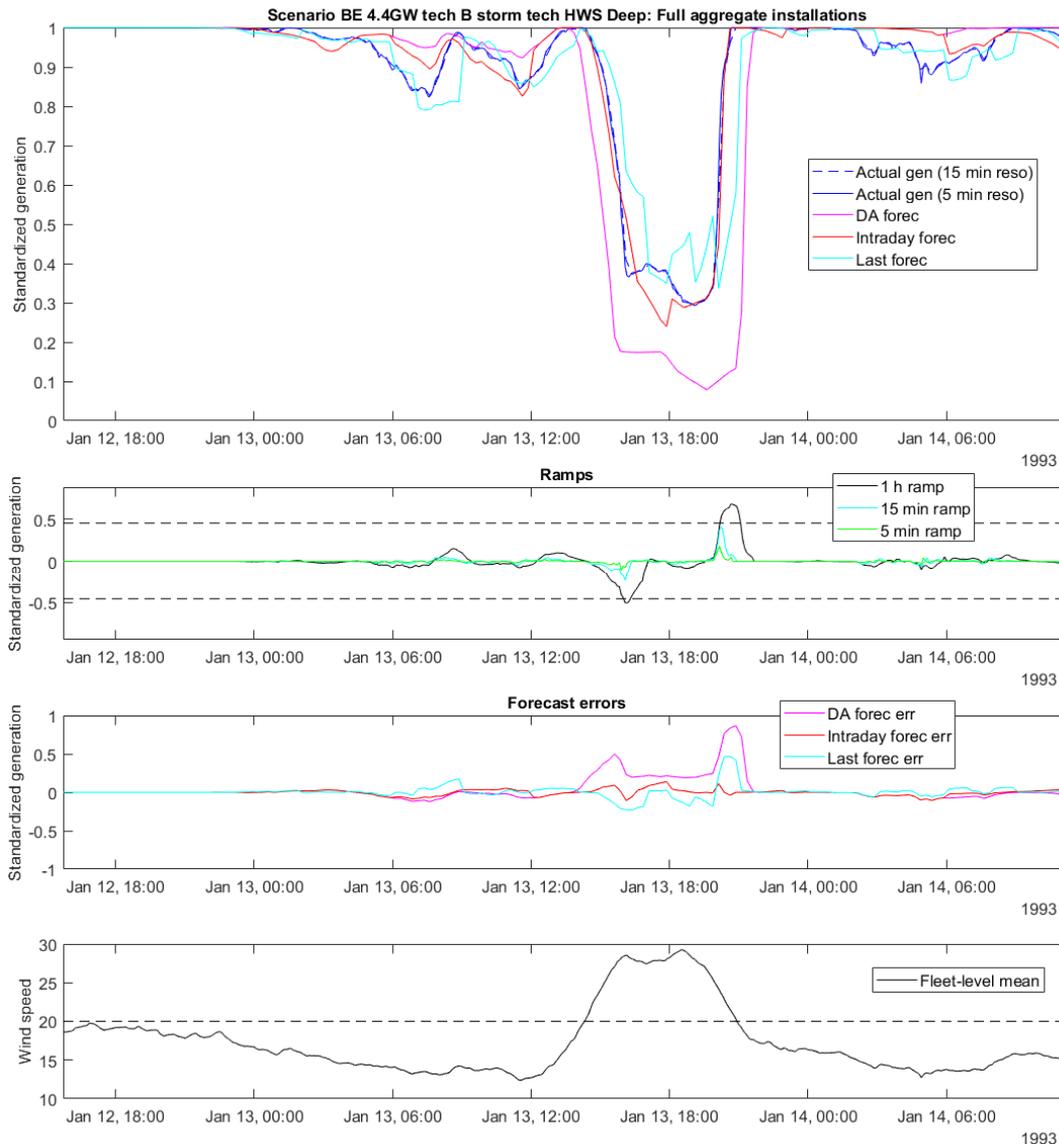


Figure 48. The time period which includes the largest simulated day-ahead (DA) forecast error for the BE 4.4. GW Tech B Deep scenario.

10.5 Conclusions on forecast errors

The fleet-level SD of standardized forecast errors decrease from the BE 2018 installations towards the 4.4 GW scenarios. This is driven by increased geographical spread of installations (no change in the forecasting accuracy of a single OWPP was assumed).

Large forecast errors are more likely during high wind speed days (fleet-level max wind speed > 20 m/s). The Deep type shows slightly lower forecast errors during high wind speeds days compared to 25 direct cut-off.

Days with high ramps (> 2 GW) show higher forecast errors, especially for “Last” forecasts. Storm days (high max wind speed and ramp > 2 GW) show higher forecast errors; however, due to relatively small amount of storm days, the estimation of forecast error distributions is challenging.

It needs to be noted that forecasts are more difficult to simulate than actual generation, as the target is not to replicate the variability due to weather, but to try to represent the forecasts by the Elia's forecast provider and to then estimate forecast behaviour in future scenarios. For this reason, the results presented for forecasts and forecast errors for the extended capacity scenarios need to be taken as representing average changes in the forecast errors resulting from different geographical installation distributions and storm shutdown technologies. The actual simulated forecast and forecast error values for an individual event are stochastic, and can be high or low due to randomness.

11. Statistical analysis on imbalance

This chapter analyses the individual BRP's imbalances and the system level imbalances based on data from the real system operation in 2018 and 2019. It includes statistical characteristics of the imbalances as well as correlations between wind power and imbalance.

11.1 Data

11.1.1 Variables

As an input for the analysis, time series with a joint 15 minutes resolution are made available by Elia for the following variables of each BRP

- Wind power production
- Wind power day ahead forecast
- Wind power intraday forecast
- Wind power last forecast
- Wind power day ahead forecast error
- Wind power intraday forecast error
- Wind power last forecast error
- Imbalance

Time series of system imbalance is also available with 15 minute resolution.

Figure 49 shows an example of wind power production, forecasts, forecast errors and imbalance. The example is chosen because it shows a clear correlation between forecast errors and imbalances, but also that there are other causes for BRP imbalances.

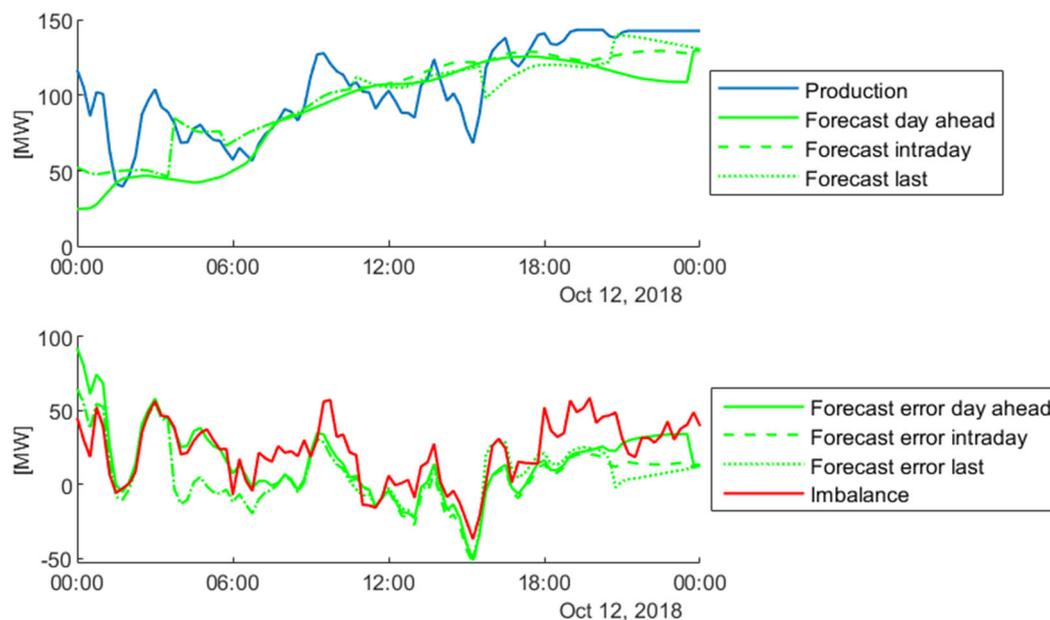


Figure 49. Example of wind power, forecasts, forecast errors and imbalance.

11.1.2 BRPs

Wind power generation and wind power forecasts are logged for the individual wind farms, but imbalances are registered at BRP level. Therefore, the contributions from wind farms to wind power generation and forecasts is summed up per BRP.

It is chosen to perform the analyses on the latest data from January 2018 to October 2019 where the installed offshore wind power capacity is increasing from 877 MW to 1535 MW. This public version of the report will show anonymized results for four BRPs operating offshore wind power plants in the Belgium system.

11.1.3 BRP sums and system level

Figure 50 shows time series of the total offshore wind power production and installed capacity in 2018-19. The installed capacity is increased from 877 MW in the beginning of 2018 to 1548 by the end of 2019.

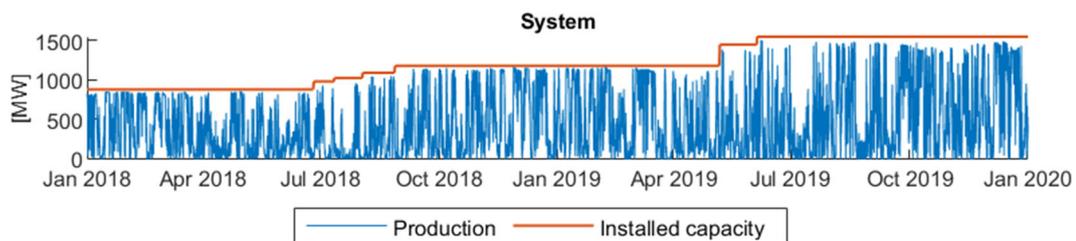


Figure 50. Offshore wind power production and capacity in Elia system 2018-19.

In order to make system level analyses in periods with fixed installed capacity, this study defines 2 data periods listed in Table 38. The table lists the included wind farms, the installed capacity and the period time for data in each data period.

Table 38. Main data for analyses periods at system level.

Period #	Installed capacity [MW]	Data period time	
		Start time	End time
1	877	System data: 01/01/2018 00.00 BRP sum data: 01/03/2018 00.00	25/06/2018 23.45
2	1178	01/09/2018 00.00	06/05/2019 23.45
3	1535	01/06/2019 00.00	31/10/2019 23.45

The reason why the start times in period 1 are different for BRP sums and system data is that some BRP imbalance data is missing in January and February 2019. Since there are 2 storm events in January 2018, it is chosen to keep January and February 2018 in the system data period

#1 and thus have this difference in the period times of BRP sum data period #1 and System data period #1.

11.1.4 Event subsets

The statistical analyses on imbalances is first performed for all the available data in the chosen periode with constant installed power. Subsequently, the same statistical analyses are repeated on subsets of the data in order to quantify the impact of high forecast errors, extreme ramping events and storm events on imbalances.

For each data period, the following data subsets are created:

- **10% highest forecast error days:** Those subsets are derived independently for each of the chosen datasets. First, the highest offshore wind power forecast errors is calculated during each day, as the difference between the maximum forecast error and minimum forecast error during the day. In the calculation of maximum and minimum forecast errors, day-ahead, intraday and last forecasts are included, although it is expected that the day-ahead forecast error normally is the largest. Then the days are sorted with respect to the forecast errors, and the days with the 10% highest forecast errors are selected for this subset.
- **20% highest forecast error days:** Those subsets are identified and selected using the same methodology as for 10% highest forecast errors but including the double amount (20%) of the highest forecast errors.
- **Extreme ramping events:** Those subsets are identified jointly at the system level in the general 2018-19 period. First, the wind power generation is normalized with the installed capacity during the period. Then the maximum (15 minutes) ramp rate is identified for each day, and days with more than 0.4 (i.e. 40%) ramp rates are selected for this subset.
- **Storm events:** Those subsets are identified jointly at the system level in the general 2018-19 period. The storm events were identified using the same algorithm which was applied to identify high wind speed events on the simulated data in clause 9.3.1. This method uses the wind speed from the MOG I platform to identify the high wind speed events. Those wind speeds are measured on the WINDSNELHEID meteorological mast which is located Easting $x=490894.62$ and Northing $y=5714599.33$ m. The height of the sensor is 43.96m above the see level which is lower than the hub heights of the wind turbines. Therefore, a simple wind shear correction has been applied to estimate wind speed at wind turbine hub height. Finally, only storm events with more than 40% ramps are selected.

With the applied storm event approach, only three storm events with power ramp downs greater than 40% were identified in 2018-19. The 40% threshold has been chosen by Elia because it conservatively matches a 2 GW ramp down of a 4.4 GW fleet. The three storm events are listed in Table 39.

Table 39. Storm events above 40%.

Start time	End time	Pmin	PFEmin	PFEmax
03/01/2018 00.35	03/01/2018 16.00	0.047	-0.735	0.420
18/01/2018 03.25	18/01/2018 10.35	0.016	-0.432	0.470
10/03/2019 11.25	10/03/2019 21.55	0.051	-0.530	0.262

Table 40 and Table 41 show the number of events for BRP sum analyses and system level analyses respectively. The reason why there are less BRP sum events than system events in the first row is the missing BRP imbalances data as explained in 11.1.3.

Table 40. Number of events for BRP sum analyses

Offshore wind capacity [MW]	10% highest forecast errors [# days]	20% highest forecast errors [# days]	Extreme ramps [# days]	Storms [# events]
877	12	23	17	0
1535	15	31	32	0

Table 41. Number of events for system analyses

Offshore wind capacity [MW]	10% highest forecast errors [# days]	20% highest forecast errors [# days]	Extreme ramps [# days]	Storms [# events]
877	18	35	29	2
1535	15	31	32	0

11.2 Imbalance statistics

11.2.1 Individual BRP imbalances

The statistical probability density functions (PDFs) of the individual BRPs imbalances was analysed and presented in a confidential version of this report to Elia. This analysis showed very different probability density functions, but we cannot disclose the results in this public report without the risk of breaking confidentiality.

The analyses included the PDFs for all available data, for the high forecast error events ramping event and storm events subsets described in 11.1.4. In general, the tails of the PDFs of the subsets were longer than the tails for distribution of all available data indicating that the imbalances were statistically higher in the subsets than in all data. This was however not visible for storm events, which is most likely because the amount of data in this subset is very limited.

Another observation was that the width of the different BRPs PDFs were significantly different. The primary reason for this is the difference in the capacity operated by the BRPs besides the offshore wind farm.

It should also be noted that the PDFs do not show if the BRP imbalances are increasing or decreasing the total system imbalance. This requires correlation analyses as done in 11.4.

11.2.2 BRP sums imbalances

Figure 51 shows the PDFs of the imbalances of the BRP sums defined in 11.1.3. Comparing to the individual BRP imbalances in the confidential version of this report, it was clearly observed that the PDFs of the BRP sums are significantly wider than the individual BRP PDFs, meaning that the BRP sum imbalances are statistically significantly larger than the individual BRP imbalances. This is as expected because the BRP sum imbalances include contributions from all 5 BRPs.

Table 42 shows the 0.1 % percentiles and 99.9 % percentiles of the imbalances of the BRP sums. For those aggregated BRP sums, the impact of the extreme ramping and high forecast error events is even more distinct than for the individual BRPs.

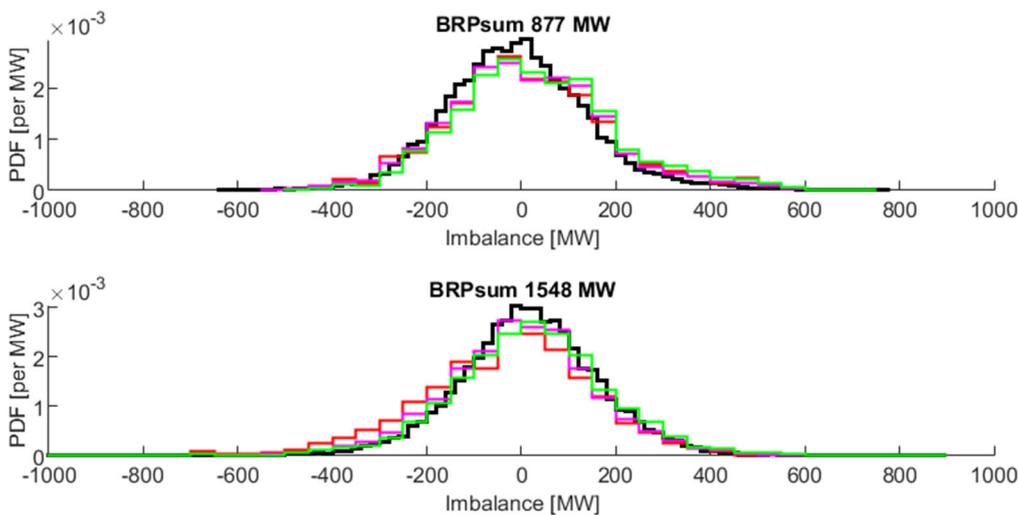


Figure 51. Probability density function for BRP sum imbalances

Table 42. 0.1 % and 99.9 % percentiles of BRP sets imbalances [MW]. Data for storms is not statistically significant.

Capacity [MW]	All valid data [MW]		FE > 10 % [MW]		FE > 20 % [MW]		Ramp > 40 % [MW]		Storm > 40 % [MW]	
	0.1	99.9	0.1	99.9	0.1	99.9	0.1	99.9	0.1	99.9
877	-514	513	-499	481	-508	531	-468	550		
1548	-691	553	-899	612	-968	597	-961	621		

11.2.3 System imbalances

Figure 52 shows the PDFs of the system imbalances. Comparing to the PDFs of the BRP sums in Figure 51, it is observed that the system imbalance PDF are a little wider, which is expected because the system imbalance also includes other contributions than the 5 offshore wind BPRs.

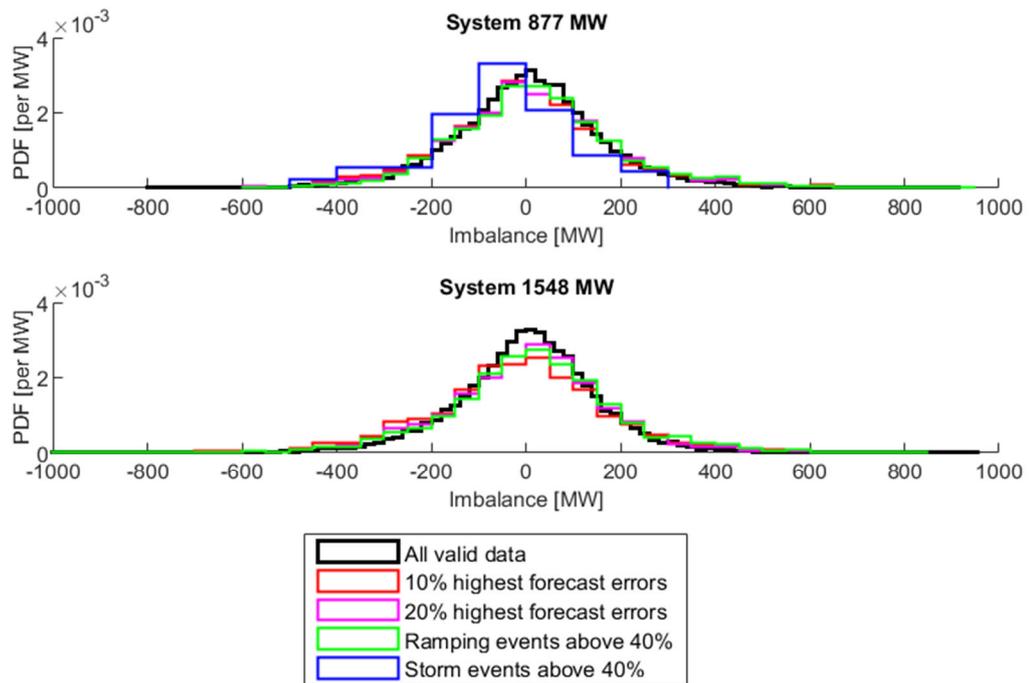


Figure 52. Probability density function for system imbalances

Table 43 shows the 0.1 % percentiles and 99.9 % percentiles of the system imbalances defined in 11.1.3. Those numbers confirm that the absolute values of the percentiles are generally larger for system imbalances than for the BRP sums above. This is also expected because the system imbalance included more contributions than the sum of the 5 offshore BRP imbalances.

Table 43. 0.1 % and 99.9 % percentiles of system imbalances [MW]. Data for storms is not statistically significant.

Capacity [MW]	All valid data [MW]		FE > 10 % [MW]		FE > 20 % [MW]		Ramp > 40 % [MW]		Storm > 40 % [MW]	
	0.1	99.9	0.1	99.9	0.1	99.9	0.1	99.9	0.1	99.9
877	-624	624	-574	724	-565	692	-564	727	-415	219
1548	-731	601	-1228	756	-1113	673	-1104	718		

11.3 Imbalance versus wind power capacity

11.3.1 Correlations between wind powers and imbalances

Figure 53 shows the correlation coefficients between wind power and imbalance for the 2 BRP sum sets, plotted as a function of the installed capacity in each of the BRP sets. The correlation coefficients are shown for wind power production, wind power forecasts and wind power forecast errors. The reason why this is straight lines is that only two periods are included in this public version.

The figure first of all shows that the correlation coefficients of the forecast errors are higher than the correlation of pure production and forecasts, which is also expected because the forecasted wind power is expected to be balanced already in the spot market. This tendency is also visible from the example time series in Figure 49.

Finally it is observed that the correlation between forecast errors and imbalances in Figure 53 does not show any no significant dependency on the installed offshore wind power capacity.

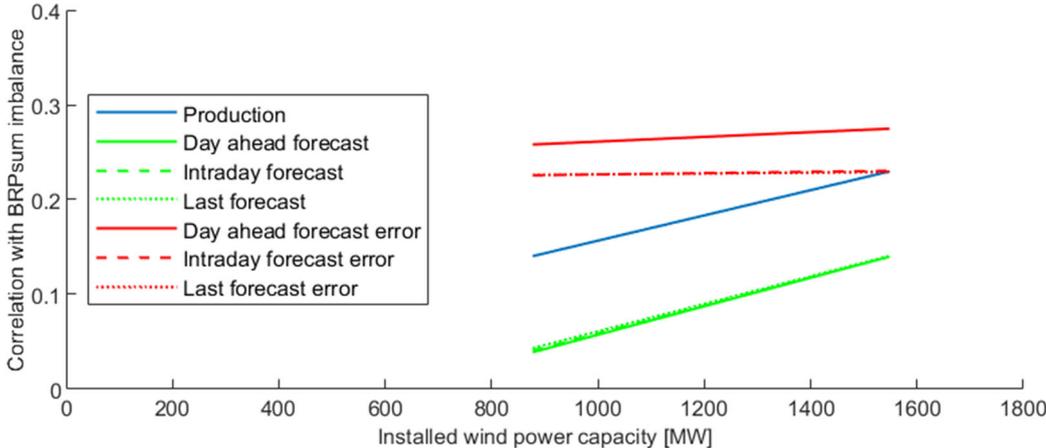


Figure 53. Correlation coefficients between wind power and imbalance for BRP sets.

Figure 54 shows the corresponding correlation coefficients with the system imbalance instead of the sum of imbalances of BRPs. The main observation is that also the system imbalance is more correlated with forecast errors than with forecasts and production. Another observation is that the correlations between last forecast error and system imbalance is increasing for increasing installed capacity, but this trend is not very strong. Finally, it is observed that the forecast error correlations with system imbalance are a little lower than correlation with sums of offshore BRP imbalances, which is as expected because the system imbalance includes other sources than the BRPs in the sets.

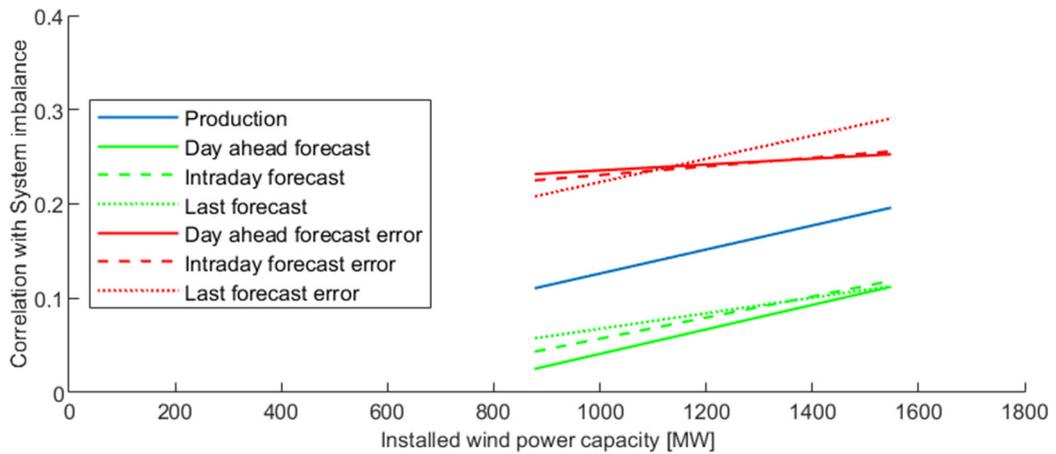


Figure 54. Correlation coefficients between wind power of BRP sets and system imbalance.

11.3.2 Forecast errors and imbalance statistics

Figure 55 shows the 0.1% and 99.9 % percentiles for system imbalance and forecast errors versus installed wind power capacity in the two selected periods. It is clearly seen how increased installed wind power increases the wind power forecast error. The impact of increased capacity on imbalances is also visible for the (lower) 0.1% percentiles but not for the (upper) 99% percentiles. It should be kept in mind that other factors than wind power forecast errors influence the system imbalance.

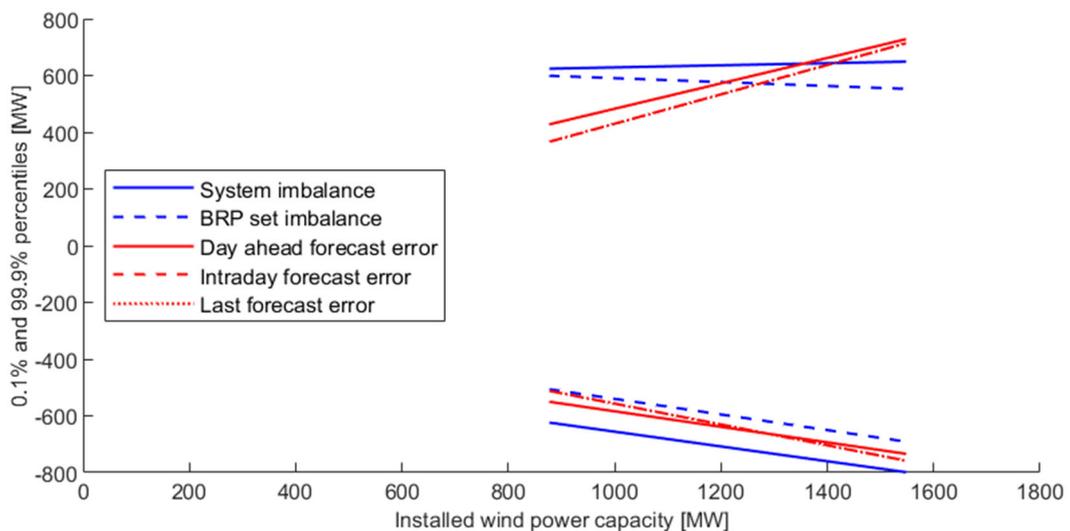


Figure 55. Observations of 0.1% (negative) and 99.9 % (positive) percentiles for system imbalance and forecast errors versus installed wind power capacity.

11.4 Correlations between forecast errors and imbalances

11.4.1 Individual BRP imbalances

Correlations can either be quantified by the correlation coefficients as it was done in 11.3.1 or by cross correlation functions which add information about the correlation when the time series are shifted against each other with a certain lag.

The cross correlation function between between BRP forecast errors and BRP imbalances are shown in Figure 56 for day-ahead forecast errors, intra-day forecast errors and last forecast errors.

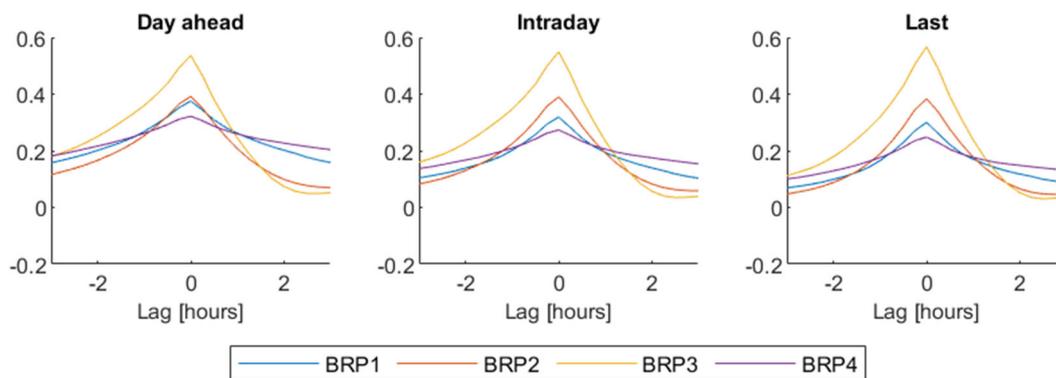


Figure 56. Cross correlation function between BRPs wind farm forecast errors and imbalances

The following observations are made:

- There is a significant difference of the correlations between forecast errors and imbalances for the different BRPs. The cross correlation function was analysed for 5 BRPs, but Figure 56 only shows the four most similar ones while the 5th had to be removed to avoid breaking confidentiality. Based on results from all 5 BRPs, we came to the general conclusion that BRPs ability to manage imbalances differ strongly between BRPs.
- The value of the cross correlation function is highest for zero lag, which confirms that the time series are properly synchronized. Initially, there was 1 sample displacement because the time in the beginning of the 15 minute value was used in one dataset and the end time in another.
- The value of cross correlation function for zero lag is per definition equal to the correlation coefficient. It is seen that the correlation coefficients are quite different for the different BRPs. The main reason for those differences is the difference in how much other generation the BRPs are operating.
- Most of the BRPs have relatively symmetrical cross correlation functions, but some converge faster to zero for positive lags. A possible interpretation of this can be that those BRPs compensate for the imbalances with an approximate response time between 15 minutes and 2 hours, but this hypothesis has not been substantiated by further analyses.

Figure 57 shows the correlation coefficients between BRPs forecast errors and imbalances for day-ahead, intraday and last forecast errors respectively. The “All valid data” correlation coefficients are calculated from BRP datasets and the other correlation coefficients are calculated from the event subsets specified in clause 11.1.4.

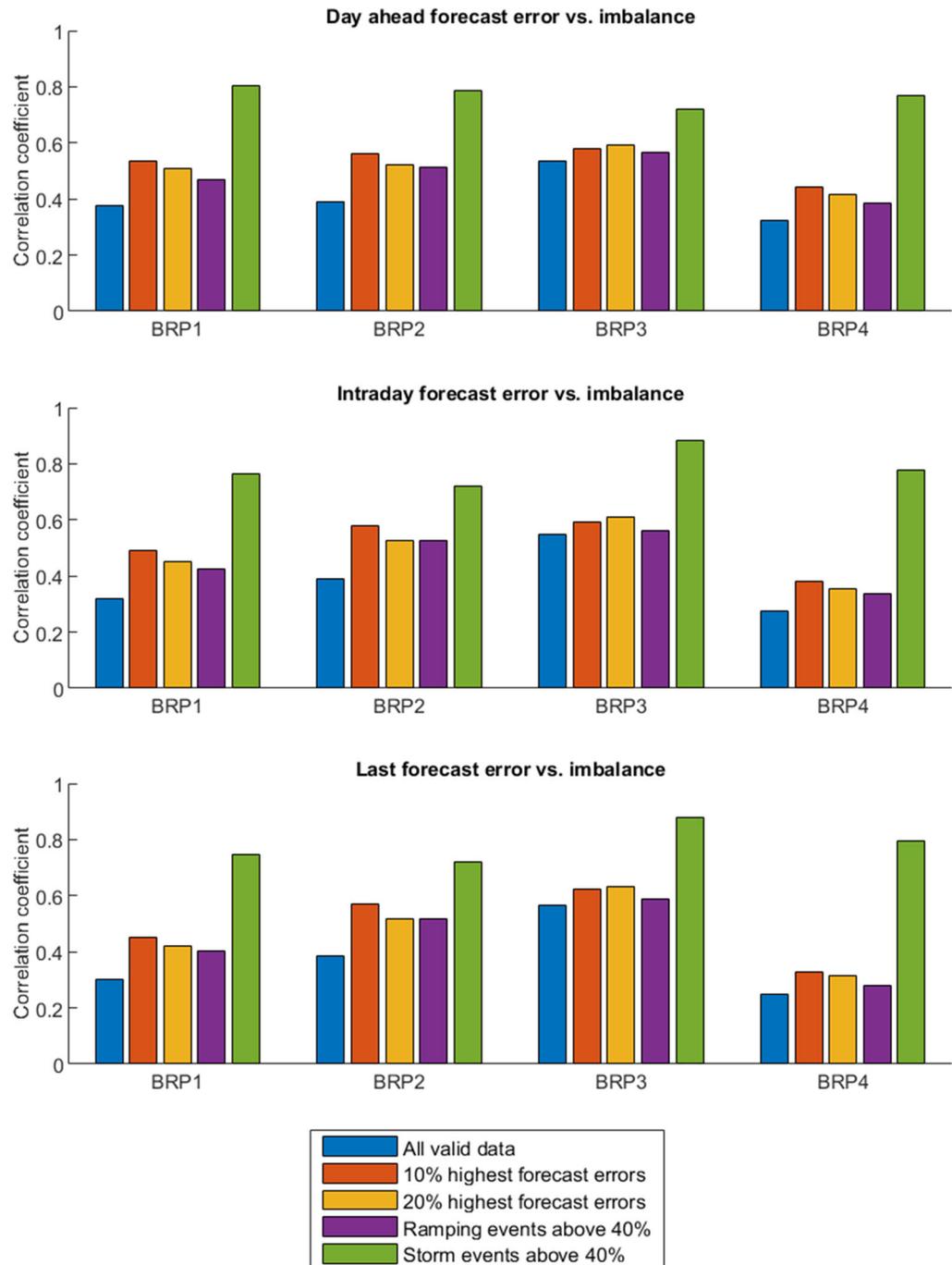


Figure 57. Correlation coefficients between BRPs forecast errors and imbalances

The correlation coefficients shown in Figure 57 are listed in Table 44.

Table 44. Correlation coefficients between BRPs forecast errors and imbalances.

BRP	All valid data			FE > 10 %			FE > 20 %			Ramp > 40 %			Storm > 40 %		
	DA	ID	Last	DA	ID	Last	DA	ID	Last	DA	ID	Last	DA	ID	Last
BRP1	0.38	0.32	0.30	0.53	0.49	0.45	0.51	0.45	0.42	0.47	0.42	0.40	0.80	0.76	0.75
BRP2	0.39	0.39	0.38	0.56	0.58	0.57	0.52	0.53	0.52	0.51	0.53	0.52	0.79	0.72	0.72
BRP3	0.54	0.55	0.57	0.58	0.59	0.62	0.59	0.61	0.63	0.57	0.56	0.59	0.72	0.88	0.88
BRP4	0.32	0.27	0.25	0.44	0.38	0.33	0.41	0.36	0.31	0.39	0.34	0.28	0.77	0.78	0.80

The main observation based on the results shown in Figure 57 and quantified in Table 44 is that the correlation coefficients are highest for the storm event subsets.

11.4.2 BRP sets imbalances

The cross correlation functions between forecast errors and imbalances for the aggregated BRP sets are shown in Figure 58 for day-ahead, intraday and last forecasts respectively. The data periods with constant installed capacity are relatively short, so the results should not be over-interpreted, but there is clearly more lag in the correlation in the 877 MW period than the 1548 MW period. The reduced lag in the 1548 MW period indicates that the forecast errors are balanced faster in that period.

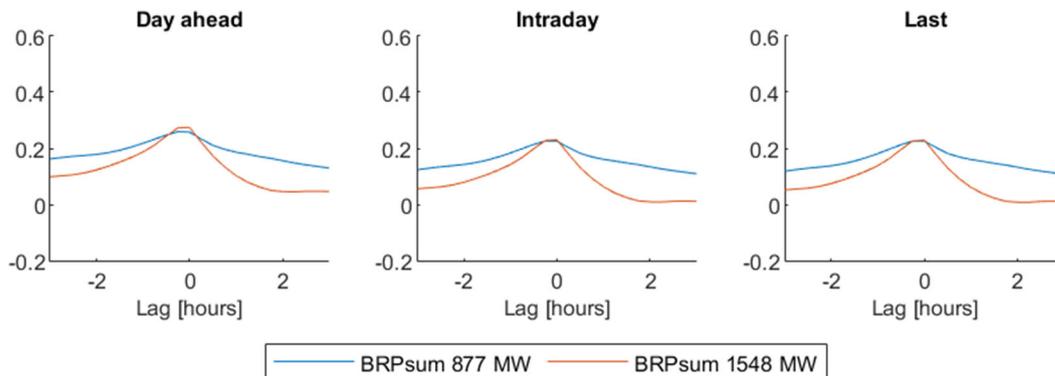


Figure 58. Cross correlation function between BRP sums forecast errors and imbalances

Figure 59 shows the correlation coefficients between aggregated BRP sets forecast errors and imbalances for day-ahead, intraday and last forecast errors respectively. The correlation coefficients shown in Figure 59 are listed in Table 45.

As for the individual BRPs, this statistical analysis is done for all available data as well as the subsets for days with highest forecast errors and extreme ramping events, and for the storm events. The impact of the extreme events is also quite significant at for this BRP sum data.

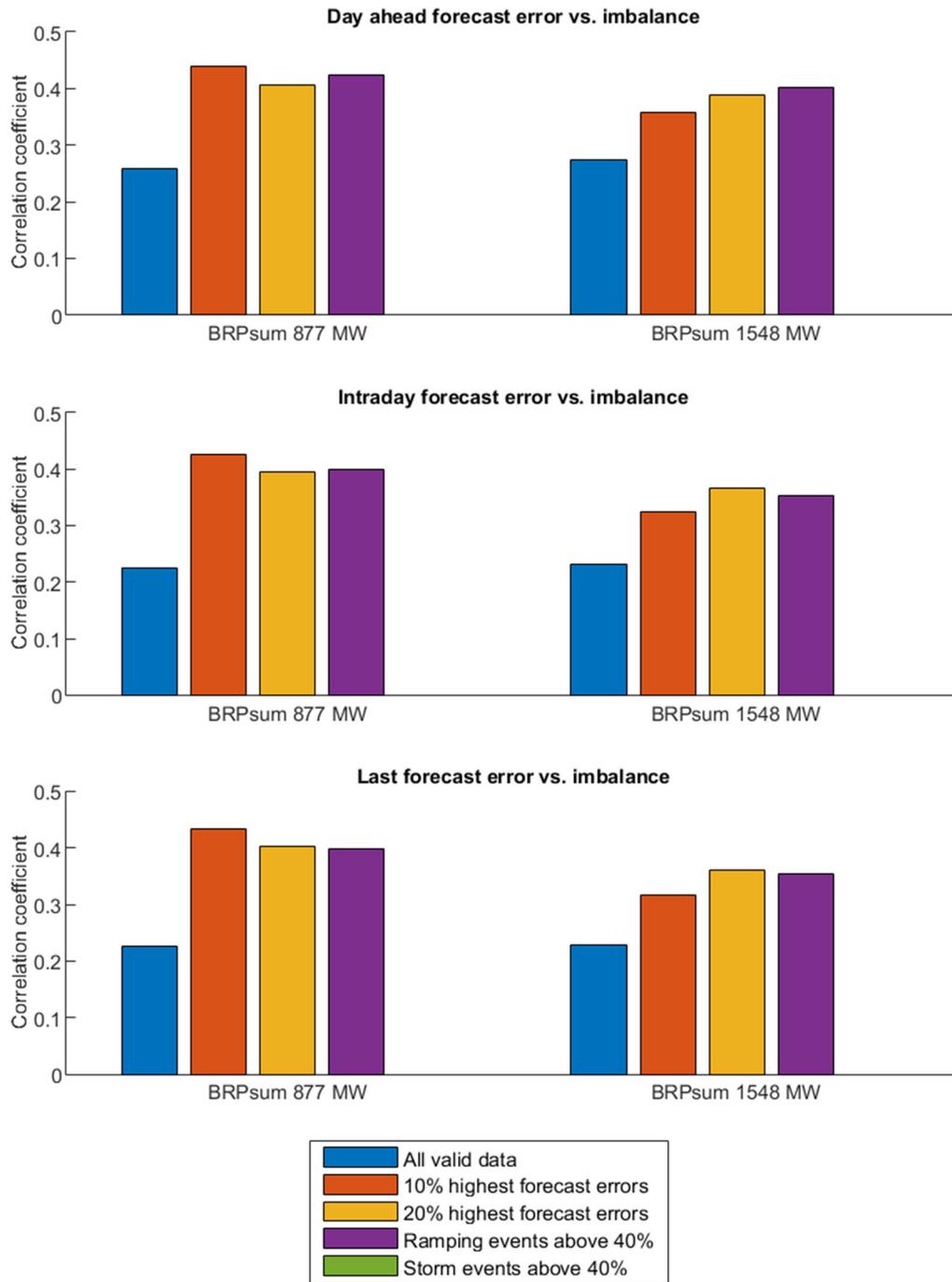


Figure 59. Correlation coefficients between offshore wind farm day-ahead forecast errors and BRP sum imbalances

Table 45. Correlation coefficients between forecast errors and imbalances of BRP sets.

Installed [MW]	All valid data			FE > 10 %			FE > 20 %			Ramp > 40 %			Storm > 40 %		
	DA	ID	Last	DA	ID	Last	DA	ID	Last	DA	ID	Last	DA	ID	Last
877	0.23	0.18	0.18	0.40	0.38	0.39	0.37	0.34	0.35	0.37	0.32	0.31			
1548	0.27	0.23	0.23	0.36	0.32	0.32	0.39	0.37	0.36	0.40	0.35	0.35			

11.4.3 System imbalance

The cross correlation functions between forecast errors and imbalances for the aggregated BRP sets are shown in Figure 60 for day-ahead, intraday and last forecasts respectively. Also here, the reduction with lack is fastest for the 1548 MW period. Another difference is that the correlation of imbalance with last forecast error is higher than for the longer forecast horizons. A positive explanation for this can be that the day-ahead and intraday balancing is working as intended.

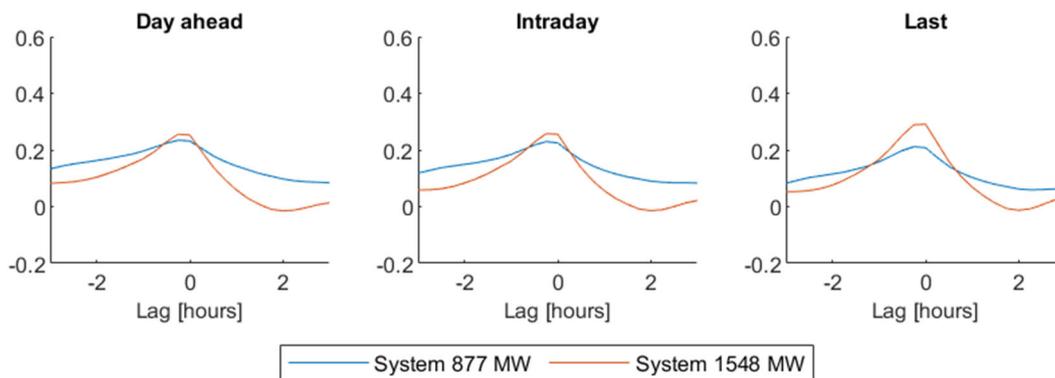


Figure 60. Cross correlation function between total wind farm forecast errors and system imbalances

The correlation coefficients between offshore wind power forecast errors and system imbalance are shown in Figure 61 and listed in Table 46.

As expected, those correlations with system imbalance are less than the correlations with BRP sum imbalances in Table 45, and as expected, this difference decreases as more BRPs are included.

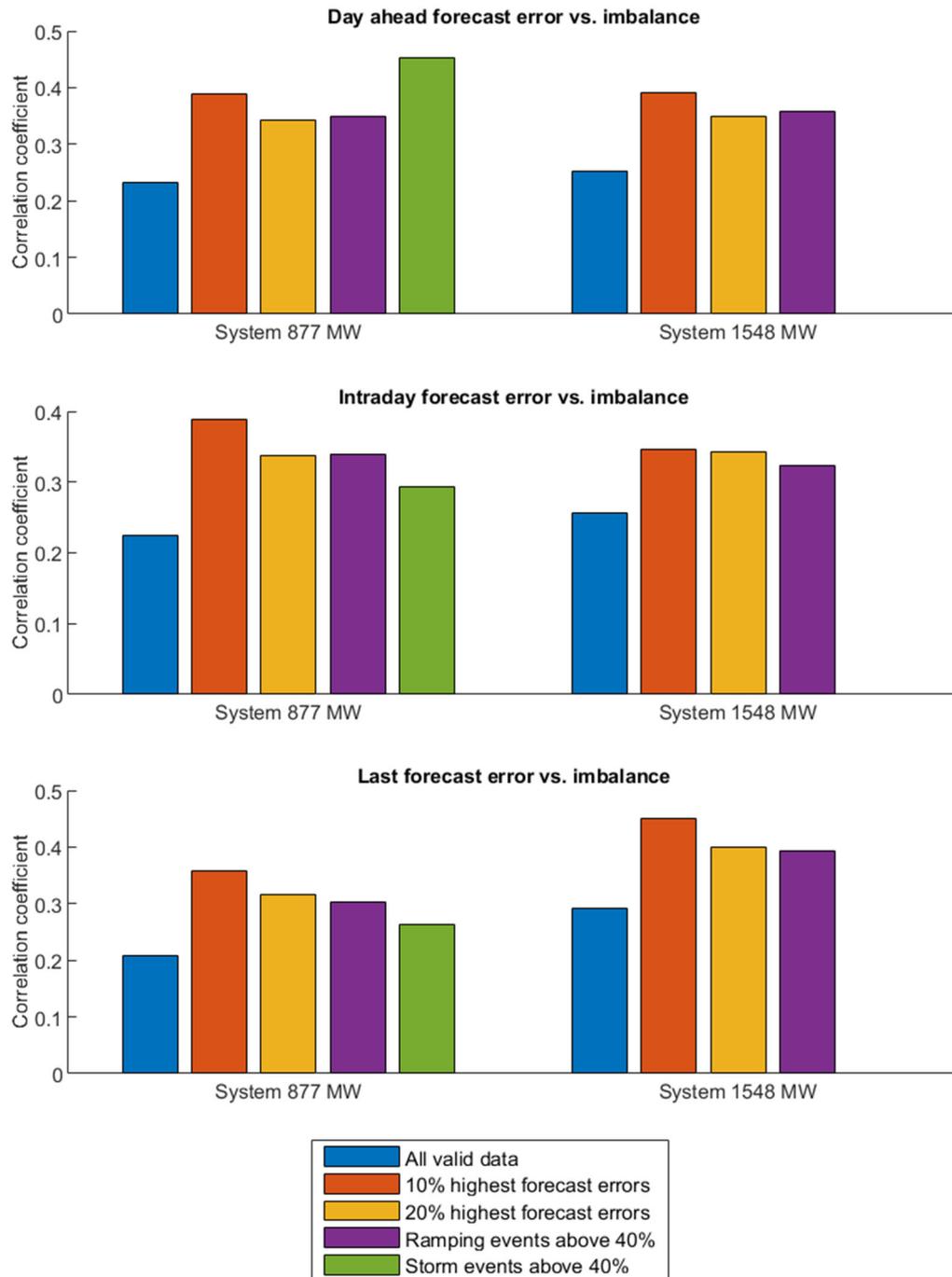


Figure 61. Correlation coefficients between offshore wind farms day-ahead forecast errors and system imbalances

Table 46. Correlation coefficients between forecast errors of BRP sets and system imbalance.

Installed [MW]	All valid data			FE > 10 %			FE > 20 %			Ramp > 40 %			Storm > 40 %		
	DA	ID	Last	DA	ID	Last	DA	ID	Last	DA	ID	Last	DA	ID	Last
877	0.23	0.23	0.21	0.39	0.39	0.36	0.34	0.34	0.32	0.35	0.34	0.30	0.45	0.29	0.26
1548	0.26	0.26	0.29	0.39	0.35	0.45	0.35	0.35	0.40	0.37	0.34	0.41			

12. Time series data provided for Elia

In addition to this report, the simulated time series from CorWind and the filtered measured data (see Section 5.4) are provided for Elia.

Simulations:

Simulated generation and wind speed data aggregated for the different scenarios, both on 5 min and 15 min resolution for 37 years are provided.

All data in the files are given in standardized generation; i.e., 1 means that the plant, or aggregate generation for the aggregate data files, is generating at full installed capacity.

Extreme ramps and storm events:

The files show how many days per year can be expected to have (at least 1) ramp event over a given limit based on the 37 years of simulations. All data are analysed in 5 min resolution (e.g., the hourly ramp means change on 5 min resolution in 1 hour). The files include sheets with all days considered, and split to days when the maximum wind speed of the day is higher or lower than 20 m/s.

The files “Extreme_ramp_events_selected” and “Storm_events_selected” report the most extreme ramp and storm cases based on the 37 years of simulations. The extreme ramp days are days when the maximum ramp (up- or down-ramp) is larger than 2 GW; the most extreme of the 5 min, 15 min and 1 h ramp defines the maximum ramp of the day. Storm days are defined as high ramp days where max wind speed of the day is above 20 m/s and where the ramp happens between the first and last time step of the day when the wind speed is above 20 m/s.

Filtered generation and forecasts for 2018-2019:

Filtered measured data from 2018 and 2019 are provided. The filtering process is explained in Section 5.4.

All data in are aggregate standardized generation; i.e., 1 means that the entire fleet (e.g., 4.4 GW of installations) is generating at full installed capacity.

As the filtering process is not valid for storm events, the times where wind speed is higher than 22 m/s have been removed from the data for future scenarios (see variable “Removed_by_DTU_because_of_storm” in the files). Wind speed data after June 2019 are not available from the OWPPs, but the wind speeds are upscaled from a single measurement point at 43.96m height above sea level from a single MET mast (WINDSNELHEID) located on the MOG platform; thus, there are more uncertainties in filtering the storm events from June 2019 onwards. As the storm events are filtered, the filter is independent of the storm shutdown technology.

It was noted that the measured forecast error data from approximately October 2019 onwards shows slightly different behaviour to the other part of the data; see Figure 62. As the data resulting from the filtering process is based on the measured data, this structural change is repeated in the data resulting from the filtering process.

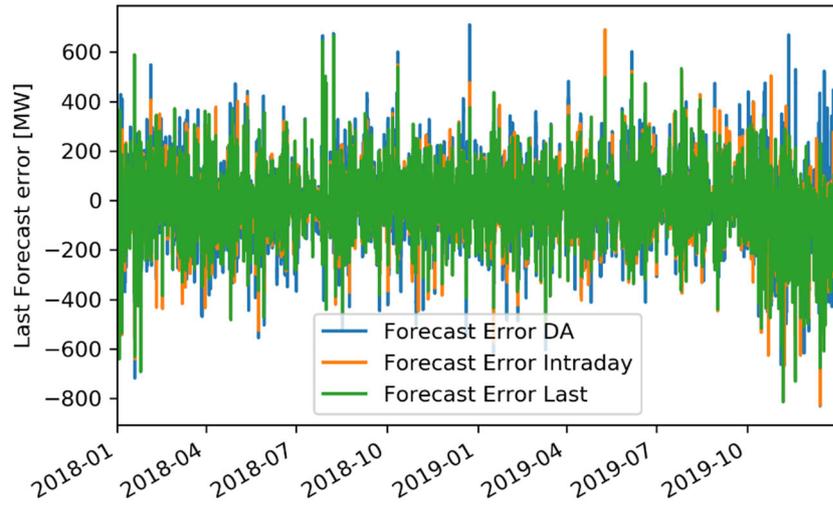


Figure 62. Forecast errors calculated from the measured data from Elia for 2018 and 2019.

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Appendix A: CFs and SDs of the additional installations

CFs and SDs of the additional installation in the different scenarios (the installations coming on top of the 2.3 GW of existing and planned installations)

			CF	SD	CF compared to BE 2018	SD compared to BE 2018
3.0 GW	Tech A	25 m/s	0.454	0.363	108%	105%
		Moderate	0.456	0.363	109%	105%
		Deep	0.457	0.363	109%	105%
	Tech B	25 m/s	0.528	0.377	126%	109%
		Moderate	0.531	0.377	127%	109%
		Deep	0.533	0.376	127%	109%
4.0 GW	Tech A	25 m/s	0.468	0.363	111%	105%
		Moderate	0.470	0.363	112%	105%
		Deep	0.471	0.363	112%	105%
	Tech B	25 m/s	0.544	0.377	130%	109%
		Moderate	0.547	0.376	130%	109%
		Deep	0.549	0.376	131%	109%
4.4 GW	Tech A	25 m/s	0.468	0.363	111%	105%
		Moderate	0.470	0.363	112%	105%
		Deep	0.471	0.363	112%	105%
4.4 GW	Tech B	25 m/s	0.544	0.377	130%	109%
		Moderate	0.547	0.376	130%	109%
		Deep	0.549	0.376	131%	109%
4.4 GW	Tech A/B	25 m/s	0.519	0.370	124%	107%
		Moderate	0.522	0.370	124%	107%
		Deep	0.524	0.370	125%	107%

All values are based on the 37 years of simulations on 5 min resolution; all data are aggregate standardized generation. 100 % availability assumed.

Appendix B: 5 min ramp statistics for the additional installations

5 min ramps statistics (standardized generation) of the additional installation in the different scenarios (the installations coming on top of the 2.3 GW of existing and planned installations).

							Compared to BE 2018			
			SD	Prct 0.01	Prct 0.1	Prct 99.9	Prct 99.99	SD	Prct 0.1	Prct 99.9
3.0 GW	Tech A	25 m/s	0.024	-0.315	-0.130	0.131	0.302	153%	167%	169%
		Moderate	0.023	-0.236	-0.125	0.126	0.234	146%	161%	163%
		Deep	0.022	-0.224	-0.123	0.125	0.221	145%	158%	161%
	Tech B	25 m/s	0.024	-0.347	-0.139	0.140	0.337	158%	179%	180%
		Moderate	0.023	-0.259	-0.132	0.133	0.258	151%	170%	172%
		Deep	0.023	-0.235	-0.130	0.130	0.237	149%	168%	168%
4.0 GW	Tech A	25 m/s	0.015	-0.196	-0.080	0.080	0.180	100%	103%	103%
		Moderate	0.015	-0.129	-0.075	0.076	0.133	96%	97%	98%
		Deep	0.015	-0.119	-0.073	0.074	0.120	95%	95%	95%
	Tech B	25 m/s	0.016	-0.222	-0.089	0.089	0.206	104%	115%	114%
		Moderate	0.015	-0.146	-0.082	0.082	0.149	99%	105%	106%
		Deep	0.015	-0.129	-0.080	0.080	0.136	98%	103%	103%
4.4 GW	Tech A	25 m/s	0.015	-0.196	-0.080	0.080	0.180	100%	103%	103%
		Moderate	0.015	-0.129	-0.075	0.076	0.133	96%	97%	98%
		Deep	0.015	-0.119	-0.073	0.074	0.120	95%	95%	95%
	Tech B	25 m/s	0.016	-0.222	-0.089	0.089	0.206	104%	115%	114%
		Moderate	0.015	-0.146	-0.082	0.082	0.149	99%	105%	106%
		Deep	0.015	-0.129	-0.080	0.080	0.136	98%	103%	103%
	Tech A/B	25 m/s	0.016	-0.208	-0.086	0.085	0.201	102%	111%	110%
		Moderate	0.015	-0.139	-0.079	0.079	0.143	98%	102%	102%
		Deep	0.015	-0.127	-0.077	0.077	0.131	97%	100%	99%

All values are based on the 37 years of simulations on 5 min resolution; all data are aggregate standardized generation.

Appendix C: 15 min ramp statistics for the additional installations

15 min ramps statistics (standardized generation) of the additional installation in the different scenarios (the installations coming on top of the 2.3 GW of existing and planned installations).

			Compared to BE 2018							
			SD	Prct 0.01	Prct 0.1	Prct 99.9	Prct 99.99	SD	Prct 0.1	Prct 99.9
3.0 GW	Tech A	25 m/s	0.051	-0.688	-0.280	0.283	0.672	144%	164%	159%
		Moderate	0.049	-0.460	-0.261	0.267	0.474	138%	153%	149%
		Deep	0.048	-0.423	-0.256	0.262	0.437	137%	150%	147%
	Tech B	25 m/s	0.053	-0.760	-0.301	0.304	0.752	150%	177%	170%
		Moderate	0.051	-0.506	-0.277	0.285	0.522	143%	163%	160%
		Deep	0.050	-0.448	-0.271	0.277	0.474	142%	159%	155%
4.0 GW	Tech A	25 m/s	0.036	-0.422	-0.186	0.189	0.409	101%	109%	106%
		Moderate	0.035	-0.286	-0.171	0.176	0.313	98%	100%	99%
		Deep	0.034	-0.255	-0.167	0.171	0.273	96%	98%	96%
	Tech B	25 m/s	0.038	-0.455	-0.208	0.211	0.451	106%	122%	118%
		Moderate	0.036	-0.316	-0.187	0.191	0.338	102%	110%	107%
		Deep	0.036	-0.279	-0.181	0.185	0.304	100%	106%	104%
4.4 GW	Tech A	25 m/s	0.036	-0.422	-0.186	0.189	0.409	101%	109%	106%
		Moderate	0.035	-0.286	-0.171	0.176	0.313	98%	100%	99%
		Deep	0.034	-0.255	-0.167	0.171	0.273	96%	98%	96%
	Tech B	25 m/s	0.038	-0.455	-0.208	0.211	0.451	106%	122%	118%
		Moderate	0.036	-0.316	-0.187	0.191	0.338	102%	110%	107%
		Deep	0.036	-0.279	-0.181	0.185	0.304	100%	106%	104%
Tech A/B	25 m/s	0.037	-0.422	-0.201	0.202	0.427	104%	118%	113%	
	Moderate	0.035	-0.301	-0.181	0.183	0.327	100%	106%	103%	
	Deep	0.035	-0.273	-0.176	0.178	0.294	99%	103%	100%	

All values are based on the 37 years of simulations on 5 min resolution; all data are aggregate standardized generation. 15 min ramps mean change in 5 min resolution data within 3 time steps.

Appendix D: 1h ramp statistics for the additional installations

1h ramps statistics (standardized generation) of the additional installation in the different scenarios (the installations coming on top of the 2.3 GW of existing and planned installations).

							Compared to BE 2018			
			SD	Prct 0.01	Prct 0.1	Prct 99.9	Prct 99.99	SD	Prct 0.1	Prct 99.9
3.0 GW	Tech A	25 m/s	0.114	-1.000	-0.604	0.641	1.000	124%	142%	138%
		Moderate	0.110	-0.811	-0.525	0.564	0.959	120%	124%	122%
		Deep	0.109	-0.736	-0.507	0.545	0.820	119%	119%	118%
	Tech B	25 m/s	0.120	-1.000	-0.668	0.696	1.000	131%	157%	150%
		Moderate	0.116	-0.839	-0.568	0.602	0.989	126%	134%	130%
		Deep	0.114	-0.762	-0.541	0.574	0.849	124%	127%	124%
4.0 GW	Tech A	25 m/s	0.097	-0.998	-0.484	0.522	0.979	105%	114%	113%
		Moderate	0.094	-0.686	-0.436	0.474	0.783	102%	103%	102%
		Deep	0.093	-0.600	-0.419	0.457	0.666	101%	99%	99%
	Tech B	25 m/s	0.102	-1.000	-0.539	0.573	1.000	111%	127%	124%
		Moderate	0.098	-0.742	-0.473	0.511	0.858	107%	111%	110%
		Deep	0.097	-0.636	-0.452	0.490	0.721	105%	107%	106%
4.4 GW	Tech A	25 m/s	0.097	-0.998	-0.484	0.522	0.979	105%	114%	113%
		Moderate	0.094	-0.686	-0.436	0.474	0.783	102%	103%	102%
		Deep	0.093	-0.600	-0.419	0.457	0.666	101%	99%	99%
	Tech B	25 m/s	0.102	-1.000	-0.539	0.573	1.000	111%	127%	124%
		Moderate	0.098	-0.742	-0.473	0.511	0.858	107%	111%	110%
		Deep	0.097	-0.636	-0.452	0.490	0.721	105%	107%	106%
Tech A/B	25 m/s	0.099	-0.978	-0.515	0.545	0.979	108%	121%	118%	
	Moderate	0.096	-0.701	-0.458	0.488	0.779	104%	108%	105%	
	Deep	0.094	-0.621	-0.439	0.469	0.695	103%	103%	101%	

All values are based on the 37 years of simulations on 5 min resolution; all data are aggregate standardized generation. 1 h ramps mean change in 5 min resolution data within 12 time steps.

Appendix E: 5 min ramp statistics for days with maximum wind speed below 20 m/s

5 min ramps: average number of days per year with at least one event when the daily max fleet-level wind speed is below 20 m/s.

			Negative ramp (GW)							Positive ramp (GW)									
			4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5
BE 2018 (877 MW)																			
Existing (2.3 GW)									0.0	0.9	0.9								
3.0 GW	Tech A	25 m/s							0.4	2.6	2.8	0.4							
		Moderate							0.1	2.2	2.5	0.1							
		Deep							0.0	2.2	2.4	0.1							
	Tech B	25 m/s							0.4	3.1	2.5	0.4							
		Moderate							0.0	2.7	2.1	0.1							
		Deep							0.0	2.6	2.1	0.0							
4.0 GW	Tech A	25 m/s							0.6	5.6	5.7	0.6							
		Moderate							0.0	4.9	4.9	0.2							
		Deep							0.0	4.8	4.8	0.1							
	Tech B	25 m/s						0.0	0.6	7.2	6.9	0.7							
		Moderate							0.1	6.4	6.0	0.2							
		Deep							0.1	6.3	5.9	0.2							
4.4 GW	Tech A	25 m/s						0.0	0.9	9.9	10.1	1.1							
		Moderate							0.3	9.1	9.4	0.4							
		Deep							0.2	9.0	9.4	0.4							
	Tech B	25 m/s						0.0	1.3	12.6	12.4	1.2							
		Moderate							0.5	11.7	11.5	0.5							
		Deep							0.5	11.6	11.5	0.5							

Days with maximum fleet-level wind speed below 20 m/s cover approximately 92 % of the simulated days (small differences between the scenarios). "Existing" refers to the 2.3 GW of installations.

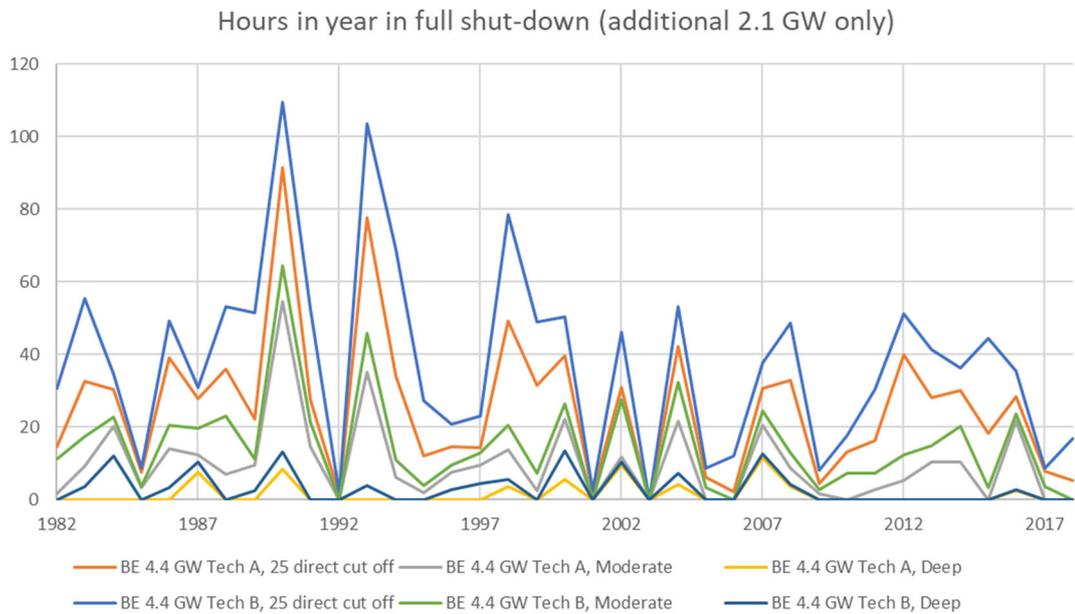
Appendix F: 15 min ramp statistics for days with maximum wind speed below 20 m/s

15 min ramps: average number of days per year with at least one event when the daily max fleet-level wind speed is below 20 m/s.

		Negative ramp (GW)									Positive ramp (GW)								
		4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0
BE 2018 (877 MW)									0.5	0.3									
Existing (2.3 GW)								5.7	63.5	72.9	6.5	0.0							
3.0 GW	Tech A	25 m/s						0.0	11.2	111.8	124.2	14.1	0.0						
		Moderate						0.0	10.9	111.6	124.1	13.7	0.0						
		Deep						0.0	10.9	111.6	124.1	13.7	0.0						
	Tech B	25 m/s						0.0	11.5	113.2	121.4	13.6	0.0						
		Moderate						0.0	11.1	113.0	121.2	13.2	0.0						
		Deep						0.0	11.1	113.0	121.2	13.1	0.0						
4.0 GW	Tech A	25 m/s						0.2	25.8	173.5	179.8	28.5	0.1	0.0					
		Moderate						0.1	25.3	173.4	179.7	28.0	0.1	0.0					
		Deep						0.1	25.2	173.4	179.7	27.9	0.1	0.0					
	Tech B	25 m/s						0.2	28.9	180.0	183.1	30.1	0.1	0.0					
		Moderate						0.1	28.4	179.7	182.8	29.5	0.1	0.0					
		Deep						0.1	28.3	179.7	182.8	29.4	0.1	0.0					
4.4 GW	Tech A	25 m/s						0.4	42.3	207.7	212.5	47.1	0.6	0.0					
		Moderate						0.4	41.9	207.6	212.5	46.5	0.6	0.0					
		Deep						0.4	41.8	207.6	212.5	46.5	0.6	0.0					
	Tech B	25 m/s						0.0	0.8	50.5	213.8	218.0	49.9	0.9	0.0				
		Moderate						0.0	0.8	50.0	213.6	217.8	49.2	0.8	0.0				
		Deep						0.0	0.8	49.9	213.6	217.8	49.1	0.8	0.0				

Days with maximum fleet-level wind speed below 20 m/s cover approximately 92 % of the simulated days (small differences between the scenarios). "Existing" refers to the 2.3 GW of installations.

Appendix G: Number of hours per year in full shut-down (additional 2.1 GW only)



Appendix H: Intraday forecast errors for days with maximum wind speed above 20 m/s

Intraday forecast errors: average number of days per year with at least one event when the daily max fleet-level wind speed is above 20 m/s.

			Negative forecast error (GW)							Positive forecast error (GW)									
			4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5
Existing (2.3 GW)								0.0	0.9	8.3	15.5	13.6	6.8	0.6	0.0				
3.0 GW	Tech A	25 m/s						0.4	2.9	13.5	19.1	17.5	12.1	2.4	0.2				
		Moderate					0.0	0.3	2.6	11.4	17.6	15.9	10.0	2.0	0.3	0.0			
		Deep					0.0	0.3	2.3	11.1	17.5	15.7	9.5	1.5	0.2				
	Tech B	25 m/s						0.2	2.5	14.5	20.4	18.7	12.6	2.1	0.1				
		Moderate					0.0	0.2	2.5	11.9	18.3	16.6	10.4	2.0	0.2				
		Deep					0.0	0.3	2.2	11.4	17.9	16.2	9.6	1.4	0.2				
4.0 GW	Tech A	25 m/s				0.1	0.6	2.4	6.7	16.0	20.2	18.9	14.5	6.0	2.5	0.6	0.1		
		Moderate				0.0	0.3	1.4	4.8	13.6	18.4	17.2	12.2	4.2	1.0	0.3	0.1		
		Deep				0.0	0.2	1.0	4.1	13.2	18.2	17.1	11.6	3.1	0.4	0.1			
	Tech B	25 m/s				0.0	0.6	2.9	7.8	17.5	22.2	20.3	16.0	6.3	2.6	0.4	0.0		
		Moderate				0.0	0.3	1.4	5.2	14.0	19.4	18.3	12.9	4.1	1.3	0.3	0.1		
		Deep					0.2	1.0	4.1	13.2	19.1	18.0	11.9	2.8	0.5	0.1	0.0		
4.4 GW	Tech A	25 m/s			0.0	0.3	1.5	3.5	8.3	17.0	21.0	19.3	15.6	7.1	3.3	1.6	0.3	0.1	
		Moderate			0.0	0.1	0.7	2.0	5.7	14.5	19.1	18.0	13.4	5.1	1.5	0.4	0.2	0.1	
		Deep			0.0	0.1	0.4	1.4	5.1	14.2	18.9	17.8	13.0	3.9	0.6	0.2	0.0		
	Tech B	25 m/s				0.4	1.7	4.5	9.6	18.7	23.2	21.4	17.1	7.7	3.6	1.9	0.2	0.0	
		Moderate				0.0	0.2	0.7	2.2	6.5	15.1	20.4	19.4	14.1	5.0	1.8	0.8	0.2	0.0
		Deep				0.1	0.4	1.6	5.2	14.3	20.0	19.3	13.3	3.7	0.8	0.2	0.1		

Days with maximum fleet-level wind speed above 20 m/s cover approximately 8 % of the simulated days (small differences between the scenarios). "Existing" refers to the 2.3 GW of installations.

Appendix I: Intraday forecast errors for days with maximum wind speed below 20 m/s

Intraday forecast errors: average number of days per year with at least one event when the daily max fleet-level wind speed is below 20 m/s.

			Negative forecast error (GW)							Positive forecast error (GW)										
			4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0
Existing (2.3 GW)							0.6	14.7	143.7	237.8	242.0	145.5	11.6	0.2						
3.0 GW	Tech A	25 m/s				0.0	3.2	38.0	187.9	262.5	266.3	190.8	34.8	2.0	0.0					
		Moderate				0.0	3.2	38.0	187.9	262.5	266.2	190.8	34.8	2.0	0.0					
		Deep				0.0	3.2	38.0	187.9	262.5	266.2	190.8	34.8	2.0	0.0					
	Tech B	25 m/s					2.9	37.1	188.6	264.2	267.2	190.2	33.5	1.8	0.0					
		Moderate					2.9	37.1	188.6	264.2	267.1	190.1	33.5	1.8	0.0					
		Deep					2.9	37.1	188.6	264.2	267.1	190.1	33.5	1.8	0.0					
4.0 GW	Tech A	25 m/s			0.1	1.8	15.4	79.5	227.4	283.9	284.2	227.0	75.5	12.7	1.2					
		Moderate			0.1	1.8	15.4	79.5	227.3	283.9	284.2	226.9	75.5	12.7	1.2					
		Deep			0.1	1.8	15.4	79.5	227.3	283.9	284.2	226.9	75.5	12.7	1.2					
	Tech B	25 m/s			0.1	1.8	15.2	79.6	229.4	285.4	285.1	227.8	75.4	12.5	1.1	0.1				
		Moderate			0.1	1.8	15.2	79.6	229.4	285.4	285.0	227.8	75.4	12.5	1.1	0.1				
		Deep			0.1	1.8	15.2	79.6	229.4	285.4	285.0	227.8	75.4	12.5	1.1	0.1				
4.4 GW	Tech A	25 m/s			0.5	4.3	25.2	103.1	241.8	290.4	291.2	241.3	97.9	21.6	2.5	0.2				
		Moderate			0.5	4.3	25.2	103.1	241.8	290.4	291.2	241.3	97.9	21.6	2.5	0.2				
		Deep			0.5	4.3	25.2	103.1	241.8	290.4	291.2	241.3	97.9	21.6	2.5	0.2				
	Tech B	25 m/s		0.0	0.4	4.4	25.9	103.7	242.4	291.2	290.9	241.3	97.9	21.8	2.7	0.1				
		Moderate		0.0	0.4	4.4	25.9	103.7	242.4	291.2	290.9	241.2	97.9	21.8	2.7	0.1				
		Deep		0.0	0.4	4.4	25.9	103.7	242.4	291.2	290.9	241.2	97.9	21.8	2.7	0.1				

Days with maximum fleet-level wind speed below 20 m/s cover approximately 92 % of the simulated days (small differences between the scenarios). “Existing” refers to the 2.3 GW of installations.

Appendix J: Latest forecast errors for days with maximum wind speed above 20 m/s

“Last” forecast errors: average number of days per year with at least one event when the daily max fleet-level wind speed is above 20 m/s.

			Negative forecast error (GW)							Positive forecast error (GW)									
			4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5
Existing (2.3 GW)								0.0	0.2	5.2	13.9	18.2	9.8	0.9	0.1				
3.0 GW	Tech A	25 m/s					0.0	0.0	1.4	11.0	18.6	21.8	14.6	2.5	0.2	0.1			
		Moderate					0.0	0.1	1.1	8.3	16.8	20.3	13.3	2.1	0.2	0.0			
		Deep					0.0	0.1	0.6	7.4	16.5	20.1	13.0	1.7	0.1				
	Tech B	25 m/s						0.1	1.1	12.1	20.1	23.4	15.6	2.4	0.2	0.1			
		Moderate					0.0	0.1	1.0	8.5	16.5	21.5	14.1	2.1	0.2	0.0			
		Deep					0.0	0.1	0.6	7.2	16.2	21.1	13.7	1.9	0.2				
4.0 GW	Tech A	25 m/s					0.2	2.8	6.1	14.1	19.8	22.6	17.9	5.3	1.8	0.4	0.0		
		Moderate				0.0	0.1	0.8	3.1	10.7	17.6	20.8	15.8	4.1	1.1	0.2	0.0	0.0	
		Deep					0.1	0.2	1.4	9.9	17.2	20.6	15.4	3.0	0.5	0.1	0.0		
	Tech B	25 m/s					0.2	3.0	7.8	15.4	21.6	24.9	19.8	6.5	1.8	0.3	0.1		
		Moderate				0.0	0.1	1.0	3.5	10.1	17.5	22.7	16.9	4.5	1.3	0.3	0.1		
		Deep					0.1	0.2	1.6	8.9	17.0	22.2	16.4	3.5	0.8	0.1	0.1		
4.4 GW	Tech A	25 m/s				0.1	1.6	4.0	7.4	15.8	20.7	23.1	19.3	7.4	2.6	0.9	0.2		
		Moderate				0.0	0.2	1.6	3.8	12.3	18.4	21.4	16.9	5.3	1.6	0.4	0.1	0.0	
		Deep					0.1	0.4	2.0	11.6	18.2	21.1	16.6	4.2	0.8	0.2	0.0		
	Tech B	25 m/s				0.1	1.4	4.8	9.8	16.9	22.5	26.1	21.8	9.0	2.9	0.9	0.2	0.1	
		Moderate			0.0	0.0	0.2	1.9	4.4	11.6	18.7	24.0	18.6	6.2	1.7	0.6	0.1	0.0	
		Deep					0.1	0.4	2.2	10.5	18.2	23.6	17.9	5.0	1.2	0.4	0.1		

Days with maximum fleet-level wind speed above 20 m/s cover approximately 8 % of the simulated days (small differences between the scenarios). “Existing” refers to the 2.3 GW of installations.

Appendix K: Latest forecast errors for days with maximum wind speed below 20 m/s

“Last” forecast errors: average number of days per year with at least one event when the daily max fleet-level wind speed is below 20 m/s.

			Negative forecast error (GW)							Positive forecast error (GW)										
			4.0	3.5	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.3	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0
Existing (2.3 GW)								0.0	1.6	75.1	217.2	246.9	115.5	3.2	0.1					
3.0 GW	Tech A	25 m/s						0.2	4.9	117.6	249.9	268.9	165.1	8.6	0.3	0.0				
		Moderate						0.2	4.9	117.5	249.8	268.9	165.1	8.6	0.3	0.0				
		Deep						0.2	4.9	117.5	249.8	268.9	165.1	8.6	0.3	0.0				
	Tech B	25 m/s					0.0	0.2	4.6	107.8	243.9	275.1	173.5	8.6	0.4	0.0				
		Moderate					0.0	0.2	4.6	107.6	243.9	275.1	173.5	8.6	0.4	0.0				
		Deep					0.0	0.2	4.6	107.6	243.8	275.1	173.5	8.6	0.4	0.0				
4.0 GW	Tech A	25 m/s				0.0	0.1	0.8	14.0	168.9	275.1	287.1	209.9	23.2	1.3	0.1	0.0			
		Moderate					0.1	0.8	14.0	168.6	275.1	287.1	209.8	23.1	1.3	0.1	0.0			
		Deep					0.1	0.8	14.0	168.7	275.1	287.1	209.8	23.1	1.3	0.1	0.0			
	Tech B	25 m/s					0.0	0.1	0.8	11.1	146.4	265.3	295.7	231.6	29.5	1.4	0.1	0.0	0.0	
		Moderate						0.1	0.8	11.1	146.2	265.2	295.7	231.6	29.4	1.4	0.1	0.0	0.0	
		Deep						0.1	0.8	11.1	146.1	265.2	295.7	231.6	29.4	1.4	0.1	0.0	0.0	
4.4 GW	Tech A	25 m/s			0.0	0.0	0.2	1.9	22.4	196.3	285.0	294.3	229.5	37.8	2.8	0.2	0.1	0.0		
		Moderate					0.2	1.9	22.4	196.1	284.9	294.3	229.5	37.8	2.8	0.2	0.1	0.0		
		Deep					0.2	1.9	22.4	196.1	284.9	294.3	229.5	37.8	2.8	0.2	0.1	0.0		
	Tech B	25 m/s					0.1	0.2	1.6	18.2	173.0	276.3	301.5	252.1	50.4	3.8	0.3	0.0	0.0	
		Moderate					0.1	0.2	1.6	18.1	172.8	276.2	301.5	252.1	50.2	3.8	0.3	0.0	0.0	
		Deep					0.1	0.2	1.6	18.1	172.7	276.2	301.5	252.1	50.2	3.8	0.3	0.0	0.0	

Days with maximum fleet-level wind speed below 20 m/s cover approximately 92 % of the simulated days (small differences between the scenarios). “Existing” refers to the 2.3 GW of installations.

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