Technical University of Denmark

Report on Design Tool on Variability and predictability. D2.8

WP 2: Interconnection optimisation and power plant system services. Task 2.1: Power output variability and predictability

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Report on design tool on variability and predictability

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
AS	Ancillary Services
Cluster	Wind Farm Cluster
DTOC	Design Tool for Offshore Clusters
DTU	Danmarks Tekniske Universitet
ENTSO-E	European Network of Transmission System Operators for Electricity
EERA	European Energy Research Alliance
EWEA	European Wind Energy Association
FP7	Frame Programme 7
GFS	Global Forecasting System
IWES	Institut für Windenergie und Energiesystemtechnik
(n)MAE	(normalized) Mean Absolute Error
MAG	Mean Absolute Gradient
NCAR	National Center for Atmospheric Research
NWP	Numerical Weather Prediction (system)
(n)RMSE	(normalized) Root Mean Squared Error
TSO	Transmission System Operator
VPP	Virtual Power Plant
WF	Wind Farm
WPP	Wind Power Plant
WRF	Weather Research and Forecasting
WT	Wind Turbine

EXECUTIVE SUMMARY

Wind power production is variable, following the inherent stochastic nature of the wind speed. This characteristic of wind power introduces uncertainty that has to be dealt with in the day-to-day operation. This is done, to some extent through forecasting, leading to the issue of wind power predictability. The impact of variability and predictability goes beyond operational issues in terms of balancing production and demand, affecting the capability of wind power to deliver ancillary services. Therefore, the issue of variability and predictability should be dealt with from the initial stages of wind power plants sitting and wind power cluster design.

The report presents a software tool, CorWind that allows the simulation of wind power time series that have a realistic variability. Furthermore, CorWind can simulate wind power output in different locations, taking into account the spatial correlation between them.

The second software module presented in the report is the Predictability tool, consisting in a Artificial Neural Network (ANN) trainer module to create forecasters associated with each analyzed wind farm and an interface to the Global Forecast System (GFS) Numerical Weather Prediction (NWP) system. Combining the synthetic time series from CorWind and the GFS forecasts (up to 144 hr ahead) is able to calculate several metrics to rank the forecastability of wind farm clusters based on their configurations.

The approach used to estimate the variability and predictability of potential offshore wind farm clusters is shown in Figure.

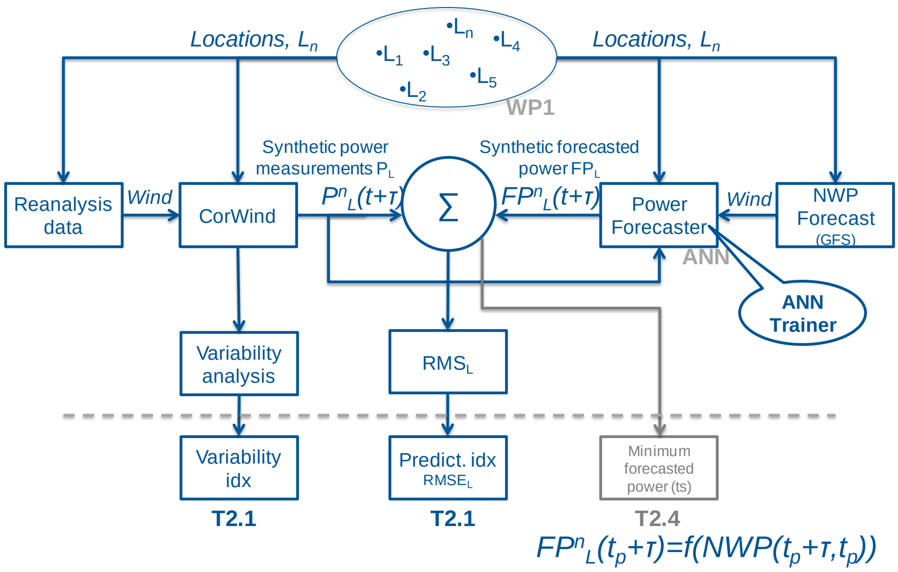


Figure Graphical overview of the approach used to calculate the variability and predictability

The use of the tools is illustrated in a case study of Kriegers Flak. Using the geographical locations of the planned wind farms, CorWind was used to simulate annual – with hourly resolution – wind power time series of each wind farm. Those time series were then used to calculate the statistics of the variability and as input to the module for estimation of the predictability. The predictability metrics during this experiment were calculated for all possible cluster combinations and then binned to present the best and worst configuration for each bin. This exercise allows understanding the relationship between the variability and predictability and provides -at the same time- an example regarding the possible kind of analysis that can be performed. Nevertheless, the use of the module in the context of EERA-DTOC not necessarily implies that the final user should create all possible cluster combinations, but it is possible to estimate the predictability only for some specific examples.

1 INTRODUCTION

According to projections by EWEA [1] the cumulative offshore wind power capacity in EU member states will increase from 5.3 GW in 2012 to 40.0 GW in 2020 and further to 150 GW in 2030. In terms of electricity production, this amounts to about 4.1 % of EU electricity consumption in 2020 and 13.9 % in 2030.

Most of this capacity will be installed in the North Sea and the Baltic Sea, leading to a rather high concentration of wind power in a limited geographical area.

Wind power production is variable, following the inherent stochastic nature of the wind speed. This characteristic of wind power introduces uncertainty that has to be dealt with in the day-to-day operation. This is done, to some extent through forecasting, leading to the issue of wind power predictability. The impact of variability and predictability goes beyond operational issues in terms of balancing production and demand, affecting the capability of wind power to deliver ancillary services. Therefore, the issue of variability and predictability should be dealt with from the initial stages of wind power plants sitting and wind power cluster design.

Wind power generation variability is not random, as it is mainly caused by large scale weather phenomena like pressure gradients in the atmosphere. Pressure gradients are correlated over long distances since they depend on high- or low-pressure areas or temperature difference prevalent in specific conditions (e.g., land-sea breeze) (Holttinen et al, January 2013).

Variability can be very high for a single wind turbine of wind power plant, but it shows significant smoothing effects when looking at larger areas. An example of this is given in Figure 1. Those are duration curves of the hourly production level over a year plotted in a descendent order.

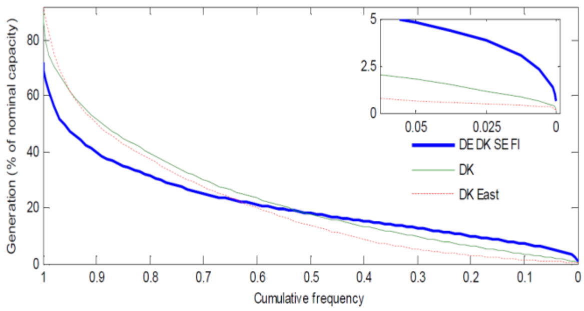


Figure 1. Aggregating wind generation over larger geographic areas decreases the number of hours of zero output and reduces the maximum power as relative to installed capacity. Cumulative frequency (i.e., duration curve) of wind power generation in areas with different size: Eastern Denmark; Denmark; and a combined area of Germany, Denmark, Sweden, and Finland (assuming an equal amount of wind power in Denmark, Sweden, and Finland while Germany has as much as the other countries put together). The inset displays the tail of the distribution more closely. Reproduced from [3].

Furthermore, variability depends also on the time scale. In general, wind power production will exhibit higher variability for longer time horizons. For power system operation, the time horizon of interest ranges from 15 minutes to several hours. An example of how variability increases with time is shown in Figure 2.

Variability is probably the most important factor that limits the ability of wind power plants to participate actively in delivering in ancillary services. The uncertainty introduced by variability is directly seen in the predictability of wind power generation, at different time scales.

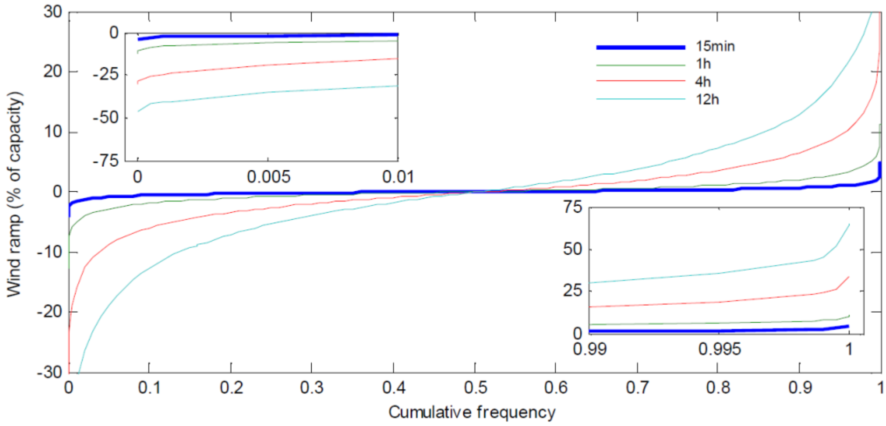


Figure 2. Smoothing effect reduces variability more at shorter time scales, as seen from cumulative frequency of ramps of different time scales in Germany for 2010–2011. Reproduced from [3].

The aim of this report is to briefly describe the design tool for assessing the wind power variability and predictability and then present a case study an outline of the specifications, the design process using these tools and procedures, and finally an analysis of the results.

1.1 Background

This report is a result of work done within the work package on *interconnection optimisation and power plant system services* (WP2) within the EERA-DTOC project [2].

The EERA-DTOC project is funded through the EU's Seventh Framework Programme (FP7) and runs from January 2012 to June 2015, and is coordinated by DTU Wind Energy. The project aims to develop a multidisciplinary integrated software tool for an optimised design of offshore wind farms and clusters of wind farms.

The project consists of 6 work packages in addition to project management:

- Wake modelling (WP 1)
- Interconnection optimization and power plant systems (WP 2)
- Energy yield prediction of wind farm clusters (WP 3)
- Integration and development of software (WP4)
- Experiments. Validation of the designed tool (WP 5)
- Dissemination and exploitation activities (WP 6)

The EERA-DTOC acronym is a combination of the European Energy Research Alliance (EERA), and Design Tools for Offshore Wind Farm Cluster (DTOC).

1.2 Tools and procedures

The tools and procedures described in this report are summarised in Table 1.

Table 1: Tools and procedures for electrical grid design.

Name	Type	Description
CorWind DTOC	software tool	Simulation of correlated wind power time series
Variability	procedure	Procedure for quantifying wind power variability
Predictability	Procedure	Procedure describing how to combine synthetic power production time series, a Numerical Weather Prediction tool and a forecaster to analyze the predictability of a cluster.

2 WIND POWER VARIABILITY

2.1 CorWind tool

The CORrelated WIND power fluctuations (CorWind) model has been developed at DTU Wind Energy (former Risø) for over a decade now. It is a software tool that allows the simulation of wind power time series that have a realistic variability. Furthermore, CorWind can simulate wind power output in different locations, taking into account the spatial correlation between them.

CorWind is an extension of the linear and purely stochastic PARKSIMU model [4] which simulates stochastic wind speed time series for individual wind turbines in a wind farm, with fluctuations of each time series according to specified power spectral densities and with correlations between the different wind turbine time series according to specified coherence functions. The coherence functions depend on frequency and space, ensuring that the correlation between two wind speed time series will decrease with increasing distance between the points. Moreover, the slow wind speed fluctuations are more correlated than the fast fluctuations. Finally, the stochastic PARKSIMU model includes the phase shift between correlated waves in downstream points, ensuring that correlated wind speed variations will be delayed in time as they travel through the wind farm. These model properties ensure that the summed power from multiple wind turbines will have realistic fluctuations, which has been validated using measured time series of simultaneous wind speeds and power from individual wind turbines in two large wind farms in Denmark[28,29].

The CorWind extension of PARKSIMU is intended to allow simulations over large areas and long time periods. The linear approach applied in PARKSIMU assumes constant mean wind speeds and constant mean wind directions during a simulation period, which limits the geographical area as well as the simulation period significantly–typically to the area of a single wind farm and to a maximum period of two hours. CorWind uses reanalysis data from a climate model to provide the mean wind flow over a large region, and then adds a stochastic contribution using an adapted version of the PARKSIMU approach that allows the mean flow to vary in time and space.

The meteorological data was produced using a mesoscale reanalysis method, which is often used for obtaining high-resolution climate or climate change information from relatively coarse-resolution global general circulation models or reanalysis. The mesoscale reanalysis uses a limited-area, high-resolution model driven by boundary conditions from the reanalysis. The strength in using the models to fill the observation gaps is that the fields are dynamically consistent and they are defined on a regular grid. Additionally, the models respond to local forcing that adds information beyond what can be represented by the observations.

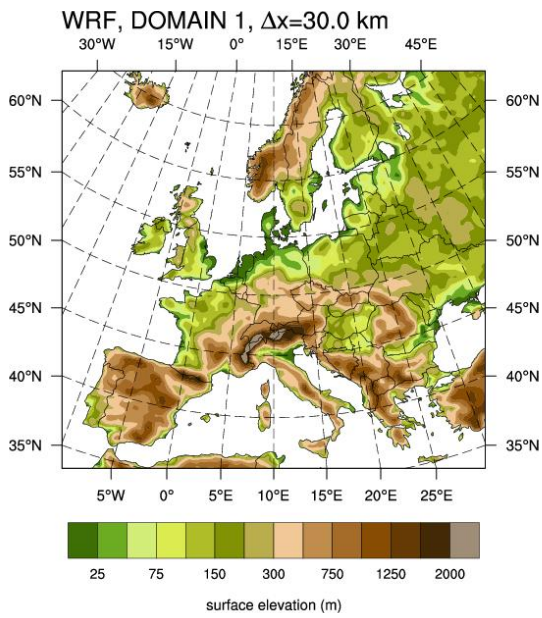


Figure 3. Domain configuration and terrain elevation used in the simulations for domain (30 km).

The mesoscale reanalysis used to generate the meteorological time series uses the National Center for Atmospheric Research (NCAR) Advanced Research Weather Research and Forecasting (ARW-WRF) model [5]. The version used is v3.2.1 that was released 18 August 2010. The model forecasts use 41 vertical levels from the surface to the top of the model located at 50 HPa; 12 of these levels are placed within 1000 m of the surface. The model setup uses standard physical parameterizations including the Mellor-Yamada (MYJ) PBL scheme [6].

The model was integrated within the domain shown in Figure 3. The model grid has a horizontal spacing of 30 km, on a polar stereographic projection with center at 52.2°N, 10°E. The domain has dimensions of 115 × 108. The simulation from which the meteorological time series are derived covers twelve years (2000–2011). Individual runs are re-initialized every 11 days. Each run overlaps the previous one by 24 h, to avoid using the time during which the model is spinning up mesoscale processes. A similar method was used and verified in [7]-[9]. Initial boundary and grids for nudging are supplied by the ERA Interim Reanalysis [10].

The model was validated against measurements from two largest – at the time – offshore wind farms in the world, namely Horns Rev 1 wind farm located in the North Sea in the west coast of Denmark and Nysted wind farm, located in the south coast of Denmark, in the Baltic Sea.

The validation was done in terms of wind farm ramp rates. The measured wind farm power is calculated in p.u. as the average power of the available turbines in each 2 hour segment. Thus, the reduction of the wind farm power due to non availability of wind turbines is removed. This choice is justified because missing data from a turbine is not necessarily indicating that the turbine is not producing power, but can also be because of failures in the SCADA system.

For each measured 2 hour segment, the average wind speed and wind direction is calculated, and a 2 hour wind farm power time series is simulated. The simulations are performed with the detailed model including low frequency fluctuations and wind farm generated turbulence.

When the ramp rates have been calculated for each set of neighbour periods n and n+1 for all segments, the ramp rates are binned according the corresponding initial power $P_{\mathrm{mean}}(n)$. This is because the statistics of the ramping will depend strongly on the initial power. For instance, the power is not likely to increase very much when it is already close to rated. A power bins size 0.1 p.u. has been selected.

The ramping is sorted in each power bin, and a duration curve is obtained. This is done for the measurements and for the simulations. As an example, the duration curves for ten minute ramp rates in the initial power range between 0.8 - 0.9 p.u. is shown in Figure 4. There is a good agreement between the simulated and the measured duration curves.

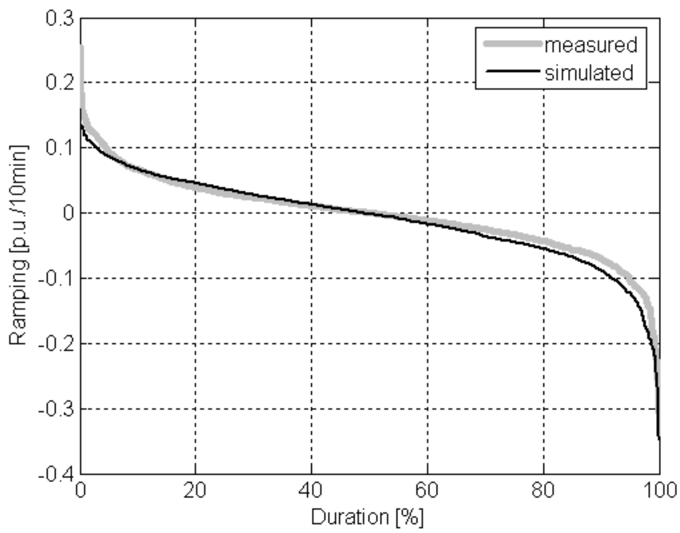


Figure 4. Duration curves of 10 minutes ramp rates in the initial power range from 0.8 to 0.9 p.u.

The most interesting point of the duration curves is the highest wind farm negative ramp rate, i.e. around 100% on the duration curve, because this quantifies the highest requirement to the ramp rates of other power plants. The wind farm positive ramp rates are not so interesting here because they can be limited directly by the wind farm main controller.

In Figure 5, the 99% percentile of the 10 minutes ramp rates duration curve for all power ranges is shown. In order to assess the model performances, both Horns Rev and Nysted simulated and measured ramp rates are plotted.

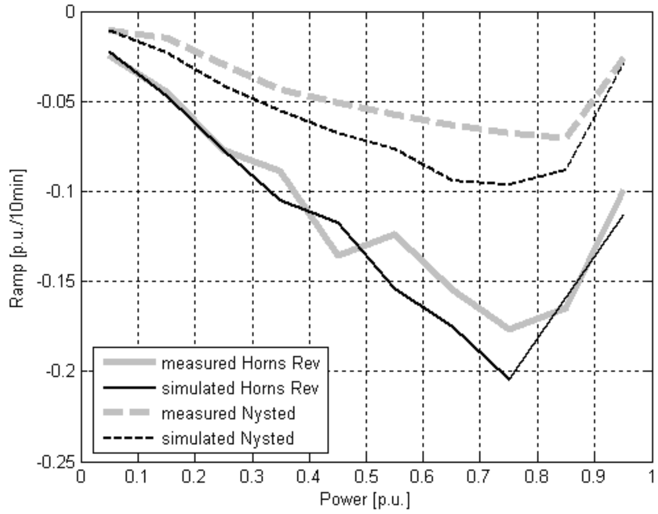


Figure 5. The 99% percentiles of 10 minutes ramp rates in all power ranges for Horns Rev and Nysted wind farm.

The 99% percentile for 30 minutes period is shown in Figure 6. The match between simulated and measured power fluctuations is similar to the 10 minutes periods, with the simulated power fluctuations still being systematically bigger than the measured ones.

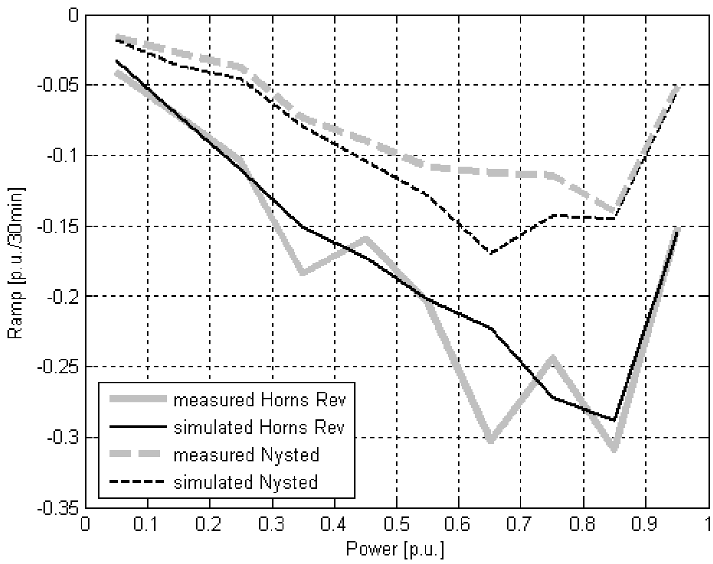


Figure 6. The 99% percentiles of 30 minutes ramp rates in all power ranges for Horns Rev and Nysted wind farms.

2.2 CorWind DTOC

This section presents the inputs for the CorWind DTOC tool.

Input parameter	Description
/Group	The group that the wind farm belongs to, i.e. country name
/Name	Name of the wind farm
/lat	The latitude of the wind farm coordinate (considered to be the median point)
/long	The longitude of the wind farm coordinate (considered to be the median point)
/PC	The power curve text file
/Tsim	Total simulation time, in seconds (default one year)
/dT	Simulation time step, in seconds (default 5 min, cannot be < 1min)
/S	Random seed for the stochastic part
/Dst	Simulation starting date, depends on the available WRF database
/pout	Name of the output file, containing the wind power time series for each wind farm considered in the simulation
/psum	Name of the output file, containing the wind power time series for each group of wind farms considered in the simulation

2.3 Wind power variability

Wind power variability occurs at all timescales. In this report, the focus is on the wind power changes from one hour to another.

3 WIND POWER PREDICTABILITY

3.1 Predictability

During the last 20 years the task of predicting the energy yield of a wind farm or a set of them has become more important as long as the penetration of the renewable energy sources has increased constantly, as shown in Figure 7.

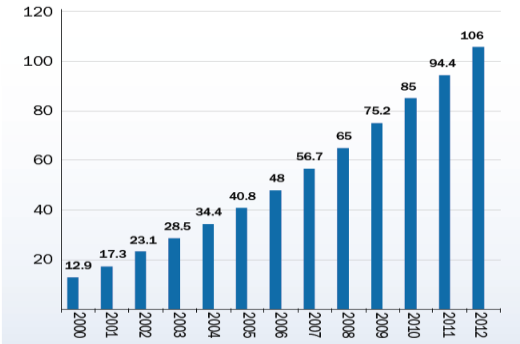


Figure 7.Cumulative wind power installations in the EU (in GW). Reproduced from [11].

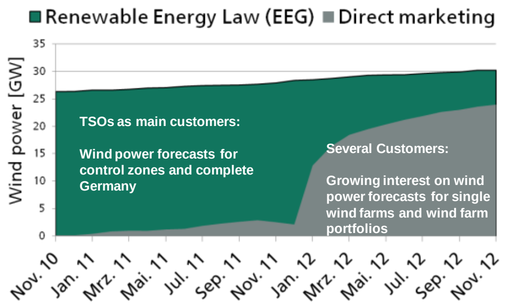


Figure 8.Changes on the mechanisms to offer energy to the system: EEG vs. Direct Marketing. Reproduced from [12].

Is expected in the coming years that wind farms operators will increase offering energy to the electricity system through direct market mechanisms, as long as some regulations (like the German Renewable Energy Law) start to disappear as promotion mechanisms. This effect is presented in Figure 8.

Under this new situation, forecasts have become more important, not only for TSOs dispatching the wind power plants and estimating the reserves, but for the asset operators, who need an accurate tool to dimension possible offers, in some cases, one or more days in advance.

According to [14] the requirements for prediction models cover mainly five time scales:

- Ultra short-term, in the range of seconds, for controlling wind turbines performing active power control.
- Very short-term, in the range of minutes (1-10 minutes ahead up to an hour), for functions such as dispatching, load following, etc.
- Short-term, in the rage of hours (0 up to 6 or 8 hours), useful for pre-dispatch, scheduling in small size power systems, etc.
- Medium-term, in the range of days (0 hours up to 7 days ahead), useful for functions such as pre-dispatch, unit commitment, trading in electricity markets and maintenance planning.
- Long-term, in the range of weeks, for maintenance planning (1-2 weeks) up to months to hydro-storage planning.

The present deliverable is focused on short-term forecasts, with a look 1 and 4 hr ahead, related with the analysis of energy and possible ancillary services markets and on the medium-term forecasts, up to 1 week ahead for maintenance purposes.

The accuracy of prediction models has been improved during the last decade and nowadays is possible to achieve a Normalized Mean Absolute Error (nMAE) of around 8% for wind farms located in flat terrains for day-ahead forecast horizons.

Martí et al. [11] defined the most common error measures. The average error of 12 different models for six different test cases is showed in Figure 9.

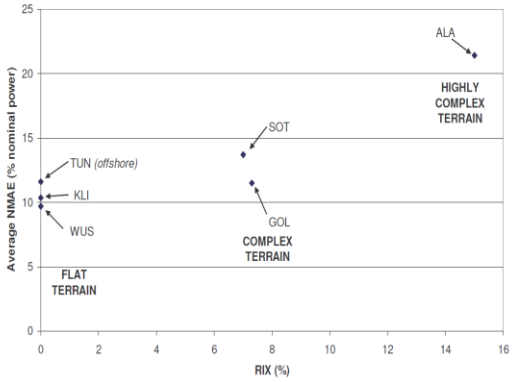


Figure 9. Average NMAE for 12 hours forecast horizon vs RIX at each test case. Qualitative comparison.

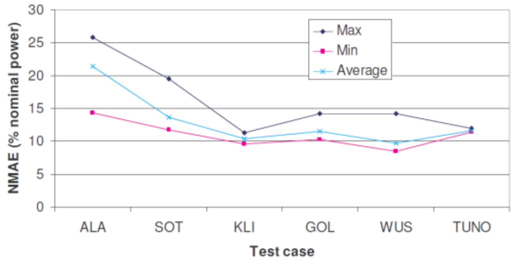


Figure 10. Average NMAE for 12 hours forecast horizon vs RIX at each test case ordered by RIX value. Qualitative comparison.

One of the test cases denominated TUN was the Tunø Knob wind farm, situated offshore, 6km of the east coast of Jutland and 10km west of the island of Samsø. This wind farm (one of the first offshore) consists of 10 Vestas V39 of 0.5 MW turbines with a total rated capacity of 5.0 MW. The RIX value for this wind farm is 0. In this case, the average nMAE was around 12%,

In a typical short-term forecast the main error source is the NWP input, being -at the same time- the limited horizontal and vertical resolution of the model, the number of weather observations, the quality of the data assimilation and the model itself, the responsible for error in a NWP.

The errors on a forecast can be of two forms:

- Level error: predicted wind or power could be higher or lower.
- Phase error: the predicted shape of an event is correct, but shifted in time.

Giebel et al. [14] recommend the several ways to reduce the mentioned source error:

- Use several NWPs: the use of more than one numerical model increases the resilience of the application and improves the accuracy of the forecast.
- Use several forecasting models: the same principle applies to the forecast model.
- Aggregate the forecast (clustering): based on smoothing effects (forecast errors are partly correlated and there is less variability of the wind farms due to the partially correlation).
- Use shorter forecast horizons for the trading: the accuracy of the forecast for shorter time horizons are better.

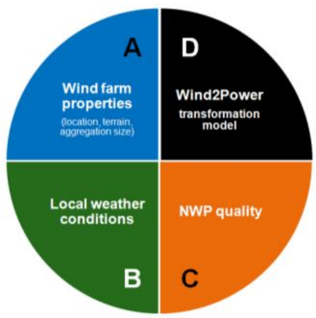
3.2 Relation between variability and predictability

The main factors that influence the forecast quality are, according to Dobschinski & Lange [12].

Forecast Quality = fct(A,B,C,D)

where the parameters A to D denote:

A : wind farm properties (like location, terrain, aggregation size, etc);
B : local weather conditions;
C : Numerical Weather Prediction (NWP) quality;
D: transformation model to transduce wind into power.



In [12], a comprehensive study of the correlation between the variability (wind power fluctuations) and predictability (forecast quality) for a single wind farm (Figure 11) and for clusters of wind farms (Figure 12). The results show that in both cases, the correlation between the Mean Absolute Gradients (MAG) of the measured 1h-power time series, defined as the absolute difference between the power in each time step, and the Root Mean Square Error (RMSE), normalized with the installed capacity, is very good.

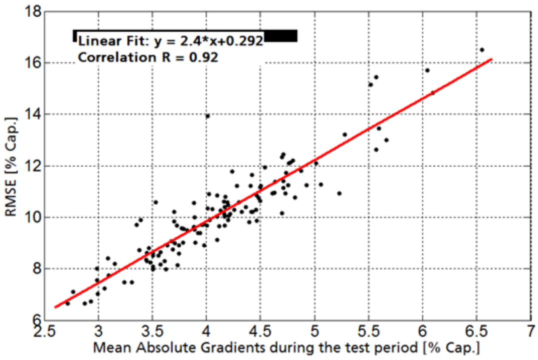


Figure 11: correlation between RSME and MAG. Reproduced from [12].

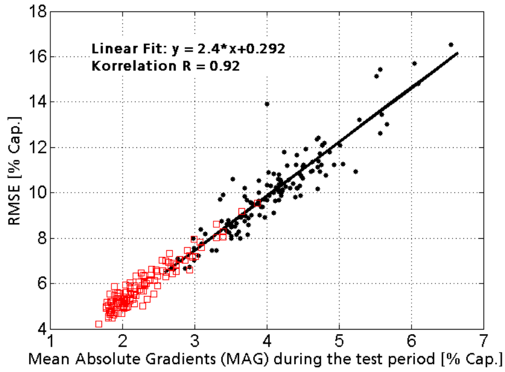


Figure 12: the correlation between RMSE and Meand Absolute Gradients (MAG), proving an excellent correlation of 0.92. Reproduced from [12].

Therefore, minimizing the wind power variability will result in better predictability. The analysis showed that wind power fluctuations are influencing the quality of the power forecast more than the NWP grid resolution.

The main outcomes are:

- Linear dependency between the RMSE of wind farm/portfolio power forecasts and the mean absolute 1h-gradients of the power time series.
- Minimizing the power fluctuations of the wind farm portfolio leads to a better forecast quality.

The methodology presented in [12] was tested onshore creating clusters randomly out from 127 selected wind farms in Germany, establishing clearly the existent relation between variability and predictability. Unfortunately, the results could not be verified on an offshore situation due to the lack of data, resulting in the impossibility of calibrating the onshore results to offshore conditions.

3.3 Approach followed in this project

As was described previously, regarding onshore wind farms and clusters large-scale evaluations of available forecasts can be used to generate a statistical model in the following form

Predictability = f(variability)

Regarding offshore wind farms and the considered lead times (intra-day, day-ahead, long-term) enough forecast data with adequate quality is not available to generate such models.

That is why it is aimed in this project to generate wind power forecasts for each wind farm within each individual designed cluster. Hence a connection to NWP data is required (i.e. GFS is available for free), implementing the automatic generation and evaluation of four forecast models per wind farm based on:

- Simulated power times series (provided by CorWind).
- NWP data of the GFS model.
- Statistical approaches: Artificial Neural Networks (ANN).

To estimate the predictability of a wind farm cluster would be enough having two models: one for short-term comparisons (i.e. 4h ahead), providing the values related with pre-dispatch and dispatch functions; and one for medium or long-term comparisons (i.e. 144h ahead) providing comparisons related with maintenance activities.

Comparing the MAE (or nMAE) for different cluster configurations would be enough to show and rank the predictability of each selected configuration.

Nevertheless, for having a better understanding of the predictability at different time horizons and because the different time series are used in the framework of the Task 2.4 as input of the process calculating the available service systems, finally four models are generated per wind farm:

- Model 1: Short-term (1h ahead). In combination with the 24h ahead model and the simulated power time series is used to calculate the available balancing power.
- Model 2: Short-term (4h ahead). It is one of the most used models for operation purposes.
- Model 3: Day-ahead (24h ahead). In combination with the simulated time series is used to calculate a possible schedule for active power for the day-ahead market as well as for the reserve market (under the assumption that the latter already exists and have a gate closure time 1 day before).
- Model 4 Long-term (144h ahead). It is useful to determine, based on different cluster configurations, the predictability for maintenance purposes.

3.4 Predictability tool

In Figure 13 is presented how the aforementioned models are created. Starting with the wind farm locations, the simulated time series of power output, correlated for all wind farms, are created by CorWind; those time series are assumed as the real power output of the analyzed wind farms. At the same time, and for the same time window, the forecasted time series of the NWP model GFS are requested.

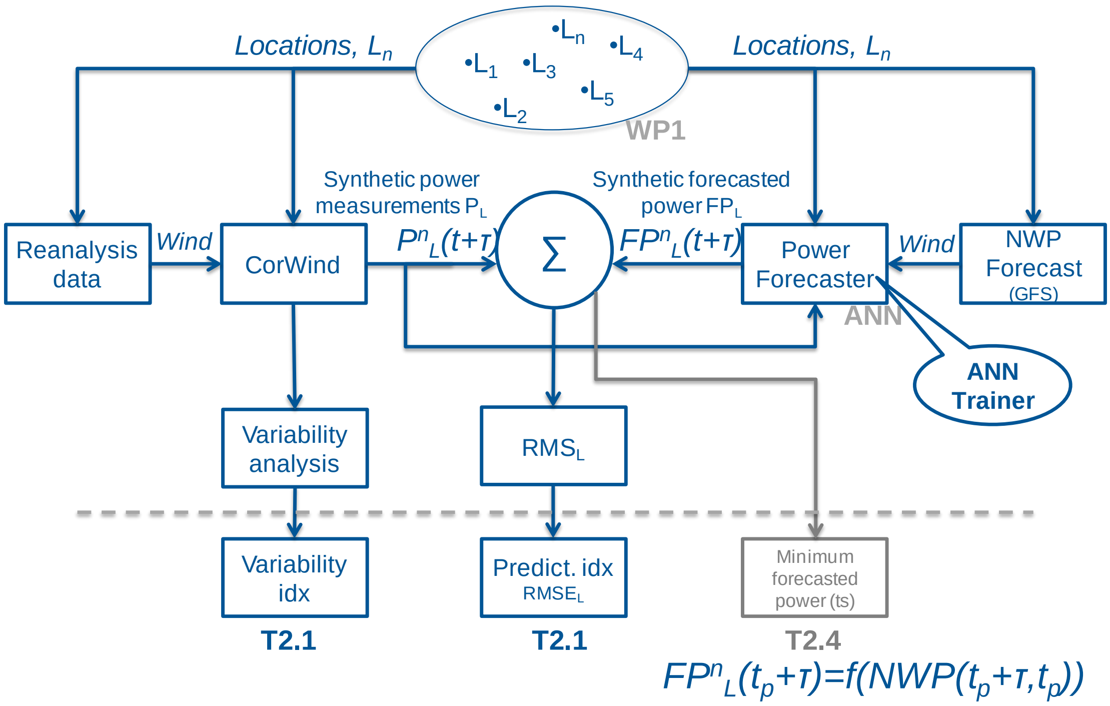


Figure 13. Graphical overview of the approach used to calculate the variability and predictability.

Then, an Artificial Neural Network (ANN) is trained using samples of this data for each wind farm that would be considered part of the cluster. Based on the trained ANN and using the retrieved data, the forecasts for each time horizons are calculated and then compared with the simulated power time series. The RMSE (or MAE) is then calculated and then a metric (unique value based on the RMSE time series) to rank the different configuration. A graphical description of an ANN is presented in Figure 14.

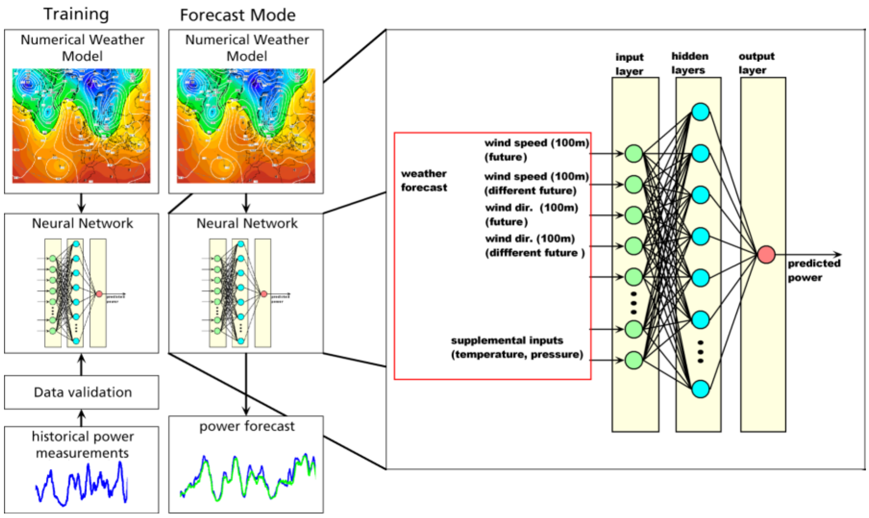


Figure 14. Scheme of an Artificial Neural Network with its two modes: training and forecast.

Computing the (n)RMSE and/ or (n)MAE is possible to compare for different wind farm aggregations the predictability of the cluster based on its configuration.
The relation between variability and predictability is also established based on the standard deviation of the synthetic power output time series provided by CorWind.

The module comprises an ANN trainer to automatically train the forecasters for each wind farm and the main module accessing the GFS model to get the corresponding time series from the NWP matching with the CorWind time series.

The module is provided as a stand-alone compiled MATLAB program.

4 STUDY CASE: KRIEGERS FLAK

This chapter describes a case study based on wind farms in the Kriegers Flak area in the Baltic Sea at the border between Denmark, Germany and Sweden. The same case study has been used throughout WP2.

4.1 Case specifications

The wind farms considered in the Kriegers Flak area are:

Table 2. List of wind farms considered in Kriegers Flak.

Country	Name	Capacity MW	Coordinates	
DK2	Kriegers Flak A K2	200	55.05	12.984
DK2	Kriegers Flak A K3	200	54.994	12.822
DK2	Kriegers Flak A K4	200	55.005	13.068
DK2	Kriegers Flak B K1	200	55.077	12.874
DE	EnBW Baltic 2	288	54.982	13.162
DE	EnBW Baltic 1	48	54.609	12.651
DE	Baltic Power	500	54.967	13.221
DE	Wikinger	400	54.834	14.068
DE	Arkona Becken Südost	480	54.782	14.121
SE	Kriegers Flak	640	55.07	13.1

The locations of the wind farms, scaled with the installed capacity, are presented in Figure 15, where red is Denmark, white is Germany and blue is Sweden.

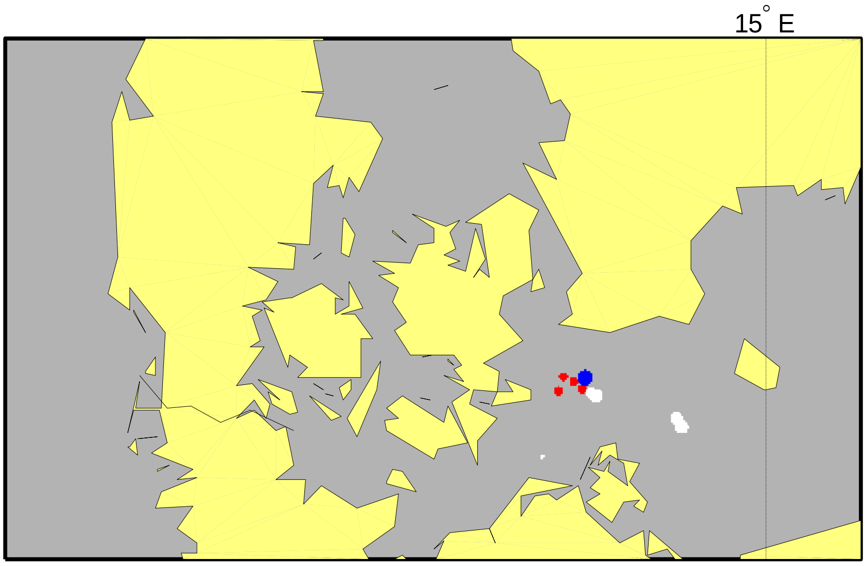


Figure 15. Locations of the wind farms.

The simulations were done using the meteorological data for 2010, resulting in a wind power production with capacities factors in the 40% zone, considered valid for offshore wind farms.

Table 3. Capacity factor calculated for each wind farm in Kriegers Flak.

Country	DK2	DK2	DK2	DK2	DE	DE	DE	DE	DE	SE
Wind farm	Kriegers Flak A K2	Kriegers Flak A K3	Kriegers Flak A K4	Kriegers Flak B K1	EnBW Baltic 2	EnBW Baltic 1	Baltic Power	Wikinger	Arkona Becken Südost	Kriegers Flak
Cap Factor	46%	45%	46%	46%	47%	42%	47%	49%	38%	47%

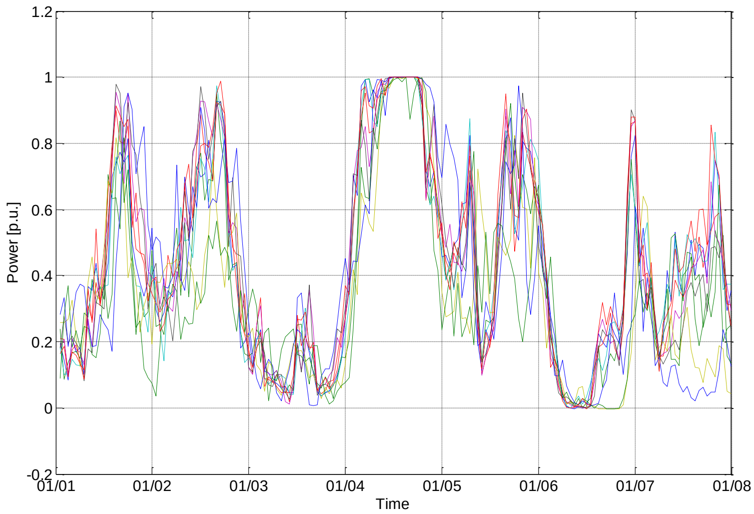


Figure 16. Wind power output for each wind farm, for week 1.

4.2 Variability analysis

In the considered case, the degrees of freedom regarding the clustering of the Kriegers Flak wind farms are limited, given that the onshore connection points are either pre-defined, or the same for a number of wind farms. Therefore, the task was to quantify the hourly wind power variability.

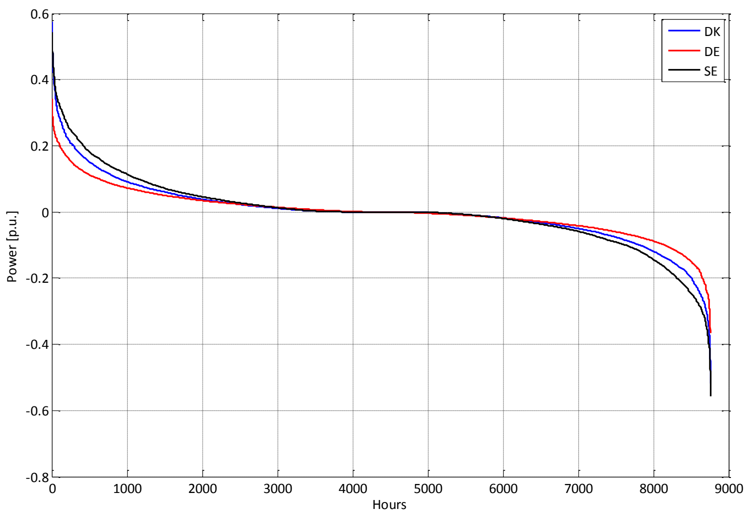


Figure 17. Hourly wind power variations for each country.

The statistics of the variability values are given in Table 4:

Table 4. Variability statistics for each country: Denmark, Germany and Sweden.

Country	DK	DE	SE
max	0.57	0.34	0.54
min	-0.52	-0.37	-0.56
std	0.10	0.07	0.11

4.3 Predictability analysis

The purpose of the experiment is showing how to choose the most predictable set of wind farms into a cluster. In this case, the most important considerations regarding the forecasts are that they shall be comparable (forecast errors must be comparable) and the time horizon shall cover one week in advance to consider the predictability of the wind farms in case of maintenance.

Based on that requirements, a neural network forecasting algorithm was trained for each synthetic wind farm listed in Table 2, at horizons of 1, 4, 24 and 144 hours, with point forecasts produced once per hour.

The GFS model is used as part of the experiment in order to make possible to predict 144 hours in advance. The specific implementation of GFS used for this experiment lacks of high accuracy due to missed data on time series and the absence of the atmospheric pressure measurement. That implies the prediction is not as accurate as in some wind energy commercial products, but -since the results are still comparable from one case to the other- the goals can be achieved.

Finally, for financial purposes the forecast quality and accuracy should be improved.

4.3.1 Forecast Error Calculation

The results of the 1 hour ahead prediction results are matching the synthetic time series exceptionally well. The possible explanation is that there is too much persistence in CorWind model.

The inputs were synthetic measured power from CorWind, along with GFS NWP forecast parameters. In a time lagged ensemble approach, the two most recent GFS forecasts were averaged. The set of inputs selected for the ANN were similar to those found in a commercial forecasting system. For all horizons, they were:

Table 5. Inputs for the ANN.

Input	Lags (hours)
wind speed upper	-1, 0, +1
wind speed lower	-1, 0, +1
wind dir upper (sin and cos components)	-1, 0, +1
time of day (sin and cos components)	0
temperature	0
power production	-3 -2, -1, 0

The power inputs were not expected to help with the 24 and 144 hour horizons, but they were retained for simplicity, and they were also not expected to cause problems, as the ANN was trained with Bayesian regularization, which limits the effect of unnecessary inputs.

The ANNs were trained on data from 05-July-2010 to 01-January-2011; and were tested on data from 01-January-2011 (one time stamp later than test) to 30-December-2012.

Since several forecast error metrics are possible and different users prefer different metrics, for sake of further analysis the RMSE, nRMSE (RMSE of normalized measured and forecasted power), MAE, and nMAE have been calculated.

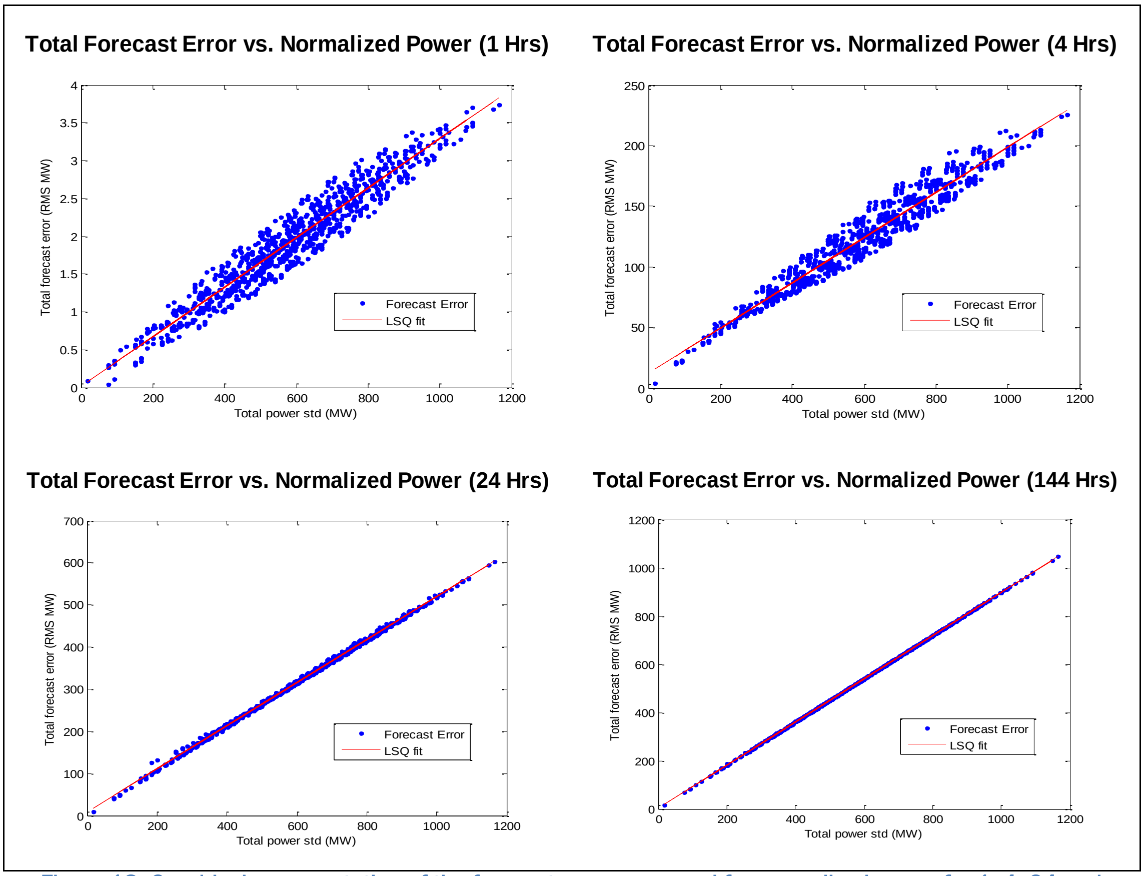


Figure 18. Graphical representation of the forecast error compared for normalized power for 1, 4, 24 and 144 hr forecasts. The Least Squares Quadratic (LSQ) fit is presented.

4.3.2 Clustering

After calculating the forecast for each single wind farm and time horizon, the wind farms were clustered in different ways in order to test the aggregated predictability. Clusters were built for every possible combination of the 10 synthetic farms: there were 10 clusters containing 1 farm each; 45 clusters of two farms; 120 of 3 farms; and so on, up to ten, where there was only one possible cluster (combinations are presented in Table 6).

Table 6. Values related with the combined wind farms.

10 WFs combined by	1	2	3	4	5	6	7	8	9	10
Number of analyzed clusters	10	45	120	210	252	210	120	45	10	1
Maximum power (MW)	640	1140	1620	2020	2308	2508	2708	2908	3108	3156

For each of those clusters, the forecast error was simulated. The wind farm forecasts made for that cluster were summed, producing a cluster forecast, and the simulated farm power productions were summed, producing a simulated cluster power output. Subtracting on from the other yielded a forecast error for each cluster was calculated.

In general, it is expected that forecast errors will decrease with the number of farms being summed, but for a given level of cluster power production, some clusters were more forecastable than others. To identify the range, the clusters were binned by their power production, and for farms within each of those bins, the clusters with the minimum and maximum forecast error were identified.

In the following figures (Figure 19 to Figure 22) the RMSE/nRMSE/MAE/nMAE line graphs are showing, along with the average forecast in each power bin.

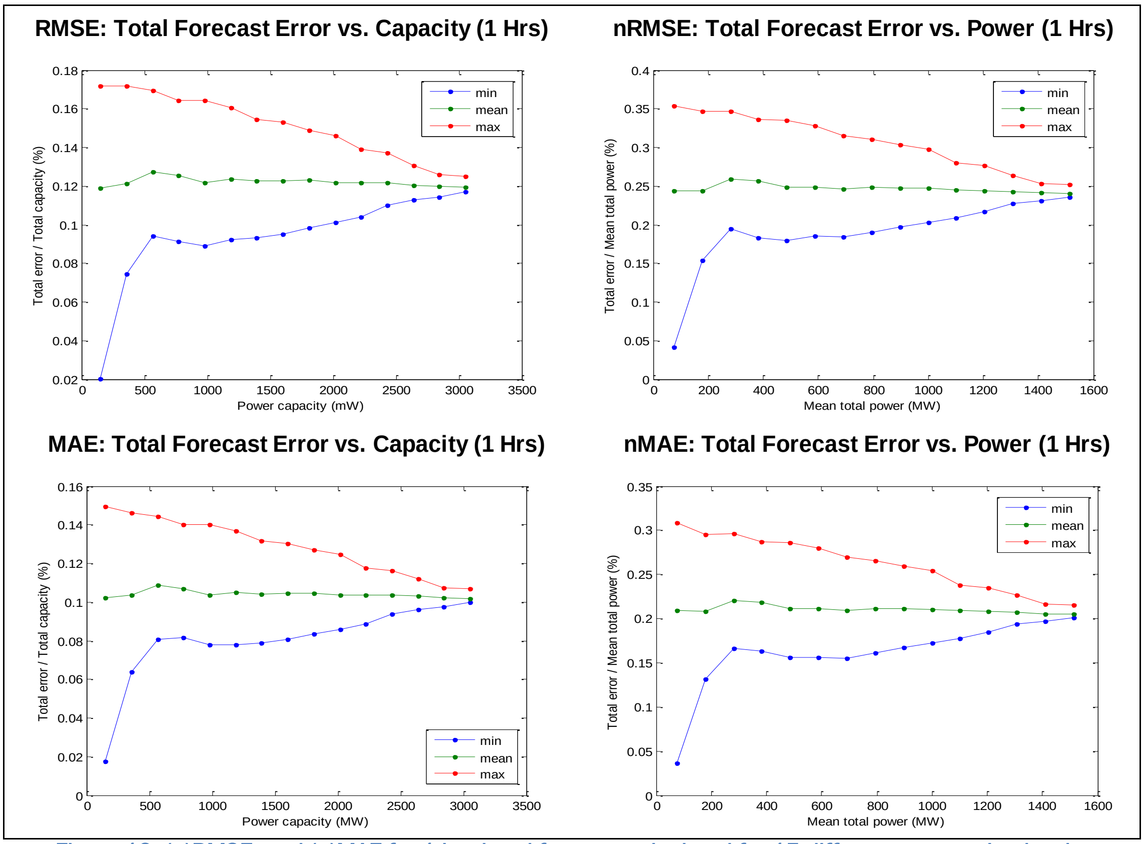


Figure 19. (n)RMSE and (n)MAE for 1 hr ahead forecast calculated for 15 different aggregation levels.

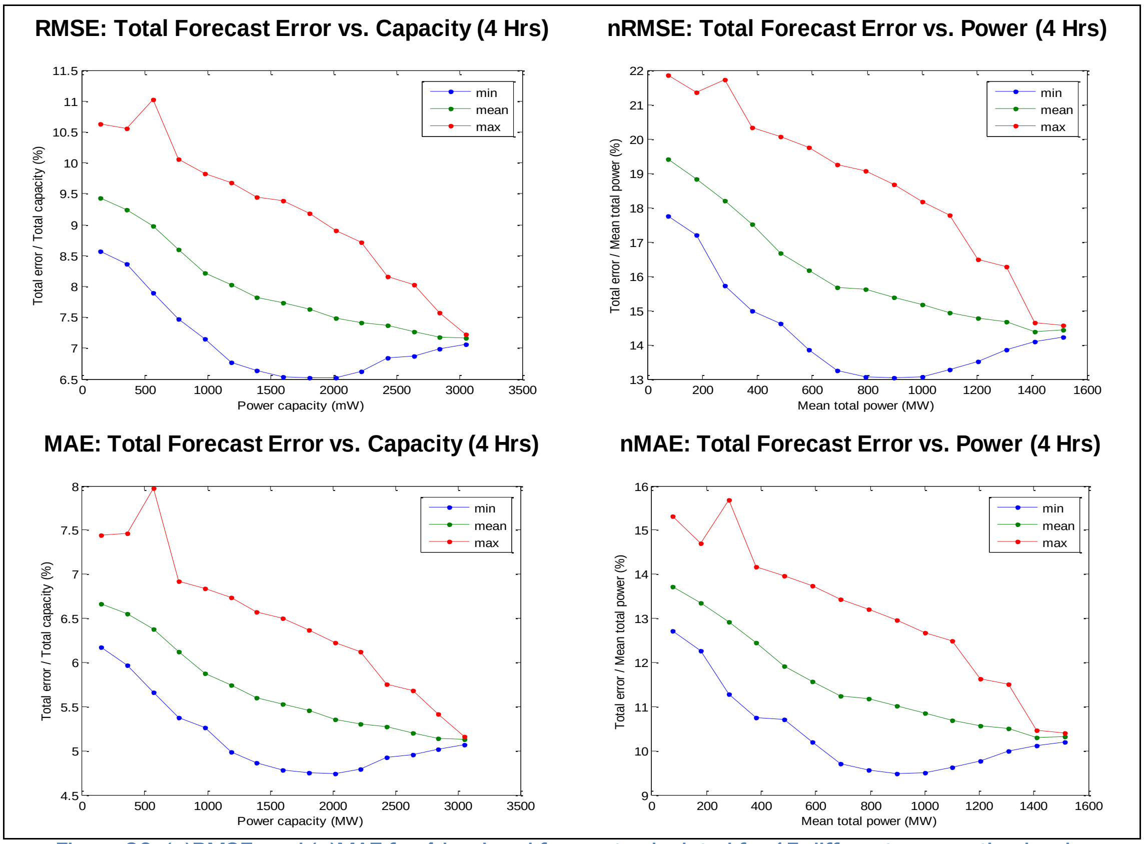


Figure 20: (n)RMSE and (n)MAE for 4 hr ahead forecast calculated for 15 different aggregation levels.

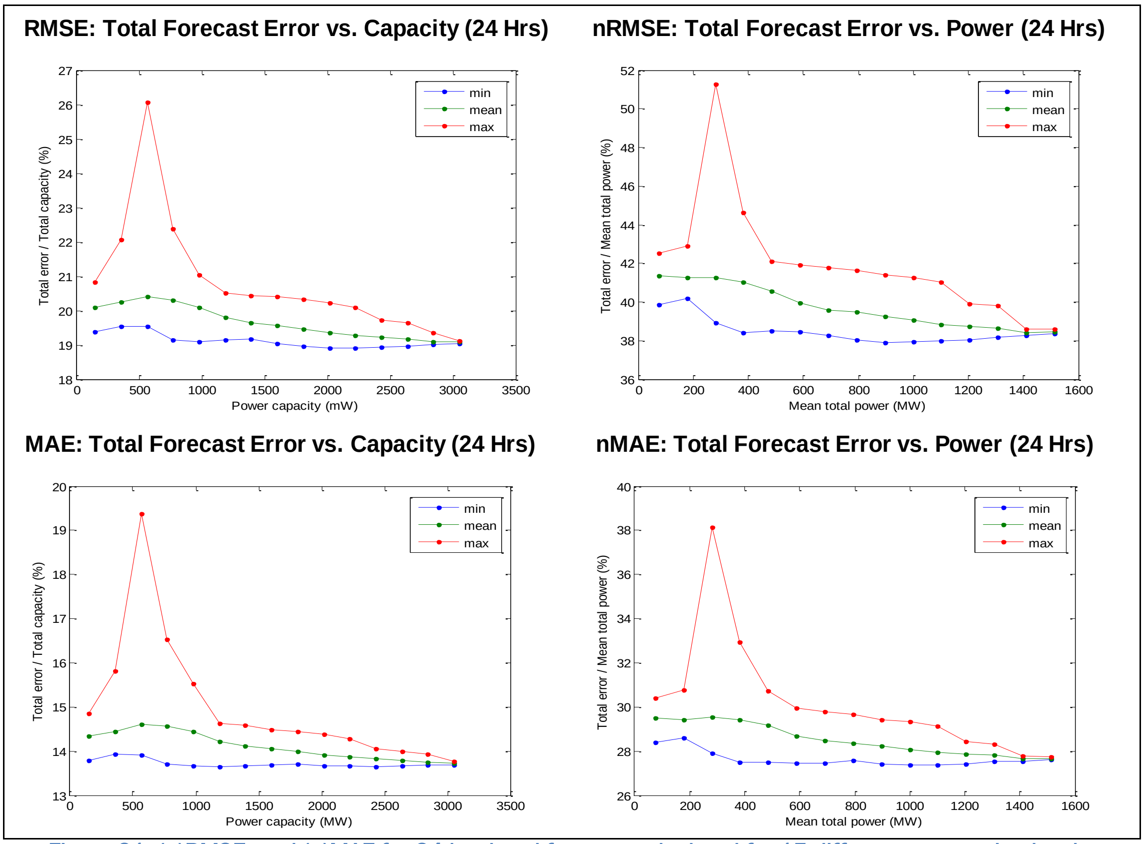


Figure 21. (n)RMSE and (n)MAE for 24 hr ahead forecast calculated for 15 different aggregation levels.

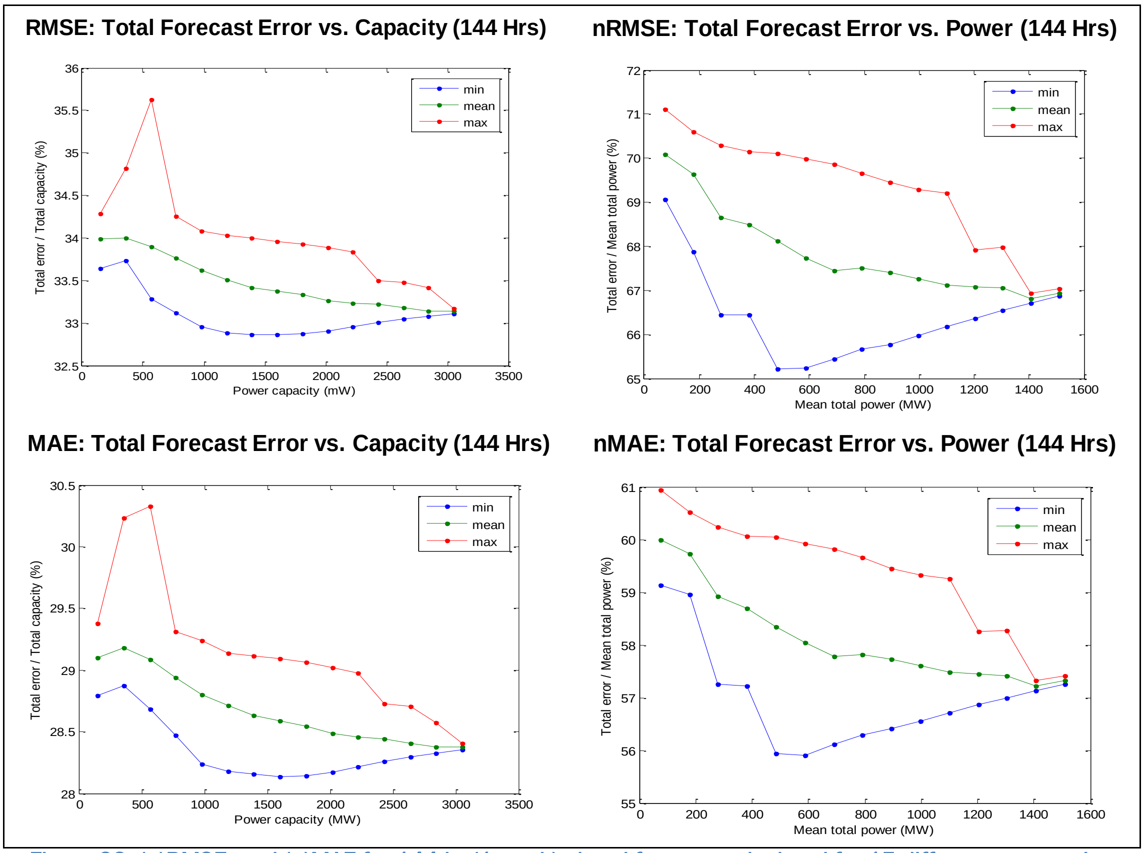


Figure 22. (n)RMSE and (n)MAE for 144 hr (1 week) ahead forecast calculated for 15 different aggregation levels.

4.3.3 Forecasting Error Results

As expected, there was a decrease in forecast error as the number of farms in a cluster increased. Also, as expected, the forecasting error was lower for clusters containing widely dispersed farms.

These tendencies can be visualized on the following maps representing with red markers the locations of farms in the cluster with the worst forecasting error; the blue are those for the best. There is one map for each forecasting horizon, cluster power production bin[1].

The relevant information presented in the maps (e.g. Figure 23 to Figure 25) is:

- The blue and red markers representing the locations;
- The forecast horizon (i.e. "1 Hr" means "one hour ahead forecasting");
- "Pt" means the power bin size;
- "Pc" means the wind farm cluster size, which should be close to Pt;
- "M" is the value of the metric used to find the min/max cluster (i.e. RMSE, MAE)

Using the bin approach 4 different metrics (i.e. RMSE, nRMSE, MAE and nMAE) were calculated for the four different forecast horizons (i.e. 1, 4, 24 and 144 hr), clustering the wind farms in 15 bins. That produces 240 possibilities that could be analyzed. In the following graphics only some illustrative situations are depicted in order to understand what is possible to infer using this tool and Table 7 contains the metric names. In the maps presented in Figure 23 to Figure 25, "Pc" is the power column above and "E" is the "Forecast error" column divided by the "Power" column.

Table 7. Calculated combinations of forecast error and power output.

Metric Name	Forecast error	Power
RMSEcap	RMSE(summed de-normalized forecast error)	summed cluster capacity
RMSEpow	RMSE(summed de-normalized forecast error)	mean sum of de-normalized power
MAEcap	MAE(summed de-normalized forecast error)	summed cluster capacity
MAEpow	MAE(summed de-normalized forecast error)	mean sum of de-normalized power

Due to the fact CorWind produces simulated farm power ranging from (0,1), regardless of the wind farm's capacity, the ANN were trained to predict this (0,1) ranged power. But, in order to simulate the actual effect of summing wind farm power, each farm's forecast was multiplied by its capacity before performing the sum. And because within each power bin the summed cluster capacities varied, they were normalized again. As a result, each forecast in the "Forecast error" column of Table 7 was divided by the quantity in the "Power" column. This "normalized de-normalized error" is comparable across the clusters in each power bin, so in that way a min and a max error cluster can be picked.

About the possible discussion regarding which metric is better, this is subject of a further analysis. Some authors divide forecast error by capacity (which makes the forecasts look better because the number is smaller) and others like to divide by mean power production. To present the results and graphics in this document the later is more meaningful, as MAE has been considered more meaningful than RMSE, too.

Figure 23 shows two maps for 4 hr ahead scenarios. The first one (on the left) shows for a cluster size of around 400 MW an improvement of 3.4% (RMSEpow 5.3%) on the predictability based on the location and number of wind farms: the example compares a cluster of two wind farms with 423 MW of aggregated power with a cluster of 410 MW constitute by 4 wind farms distributed in a wider geographical area. The second map (on the right) shows an improved forecast (MAEpow 3.5% improved and RMSEpow 5.7% better) comparing one 5-wind farm cluster of 915 MW with a second cluster consisting of 6 wind farms and 898 MW aggregated power.

[1] The clusters are rarely exactly equal to the power bin, as it had been used whatever farms sizes were available.

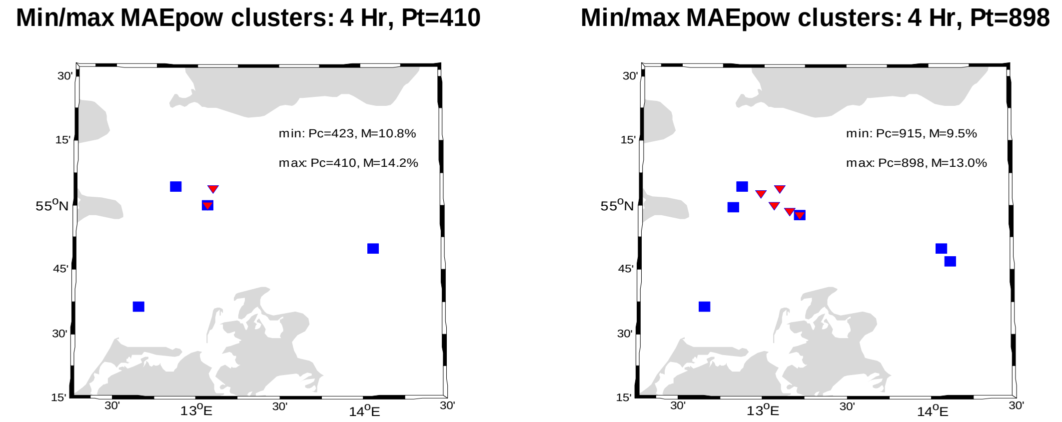


Figure 23. Examples of improvements in 4 hr forecasts due to the location of the wind farms: the locations and sizes of the wind farms have a high impact on the predictability of the power output.

On Figure 24 another two example maps are showed. The MAE metric is improved only 0.2% (RMSEpow, 0.4%) and 0.4% (RMSEpow, 0.5%) on the left- and right-hand maps respectively. In all cases, the average clustered power output is around 1470 MW, aggregating as average 9 wind farms. In such cases, the results show that some improvements are not comparable with some other considerations like the increasing complexity and cost having the wind farm located on the south-west of the map (EnBW Baltic 1, 48 MW).

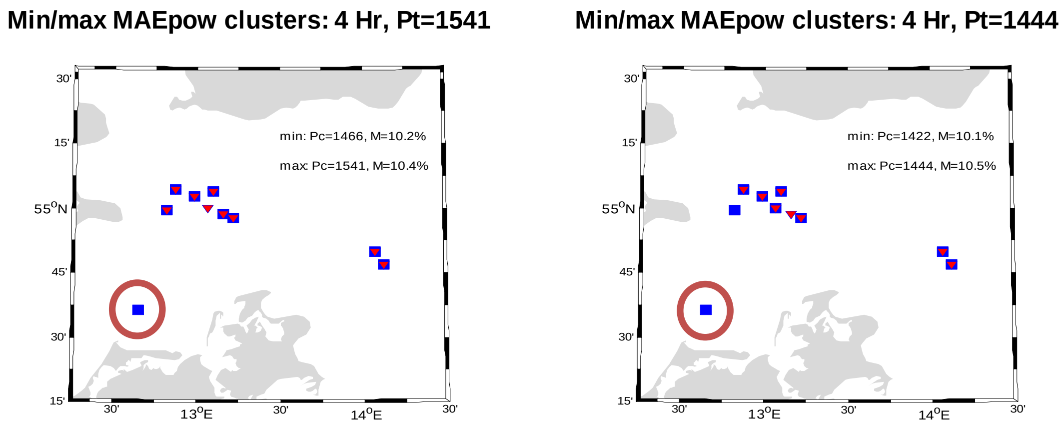


Figure 24. Examples on how to analyze forecast improvements vs. location of the wind farms: improved metrics does not justify the changes on the cluster configuration on these 4 hr ahead scenarios. The mentioned "EnBW Baltic 1" wind farm of 48 MW is marked with a red circle.

Finally, on Figure 25, two different scenarios are depicted: on the left map, again the forecast improvement (3.2% better) through a bigger number of aggregated wind farms and their geographical dispersion. On the right map, an improvement of 0.1% (RMSEpow, 0.2%) on the forecast error for sure would not justify developing a wind farm on the south-west area; instead, would be more convenient to add a new wind farm near the main development area.

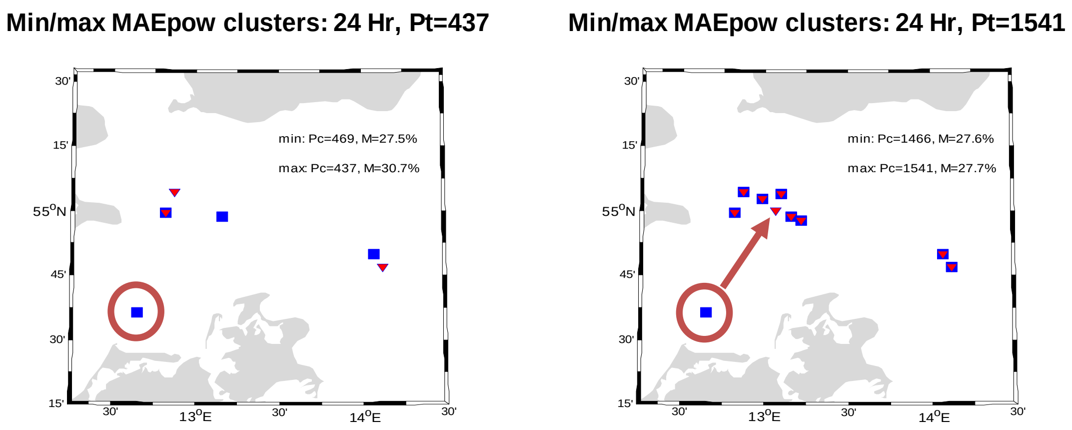


Figure 25. Comparison of two scenarios with 24 hr forecast horizon: 450 MW and 1500 MW clusters and their metric improvements against wind farm locations. On the left, developing the area in the south-west improves the forecastability by 3.2%; on the right, clearly the 0.1% improvement does not justify developing a new area instead of installing another wind farm in the already developed zone.

4.3.4 Variability

In order to assess the effect of clustering on variability, two clustering metrics were chosen: "stdPow" and "stdPowCap". For both, "variability" is the standard deviation (std) of the summed power of the wind farms in a given cluster. Similar to the forecast error line plots and maps, a measure of cluster power production was binned, and the minimum (min), maximum (max) and mean statistics were calculated on the power production standard deviation. The metrics are calculated in the following way:

- stdPow: mean summed power was binned and the y axis is std/mean Summed Power;
- stdPowCap: summed cluster capacity was binned and the y axis is std/summed Capacity. The results of this metric for different binned power and forecast horizons are presented on the graphs on Figure 26.

The standard deviations are a large percentage of the power measures (up to about 80%), but it decreases as the size of the cluster increases.

The minimum variability clusters are spatially diverse. This is shown in Figure 27, where two examples for the 24 hr time horizon are provided: On the left map, the improvement of the metric is related to the spatially diverse installations. On the right map, the comparison between the best and worst scenario for the bin reflects a minor improvement due to the fact wind farms are already geographically distributed.

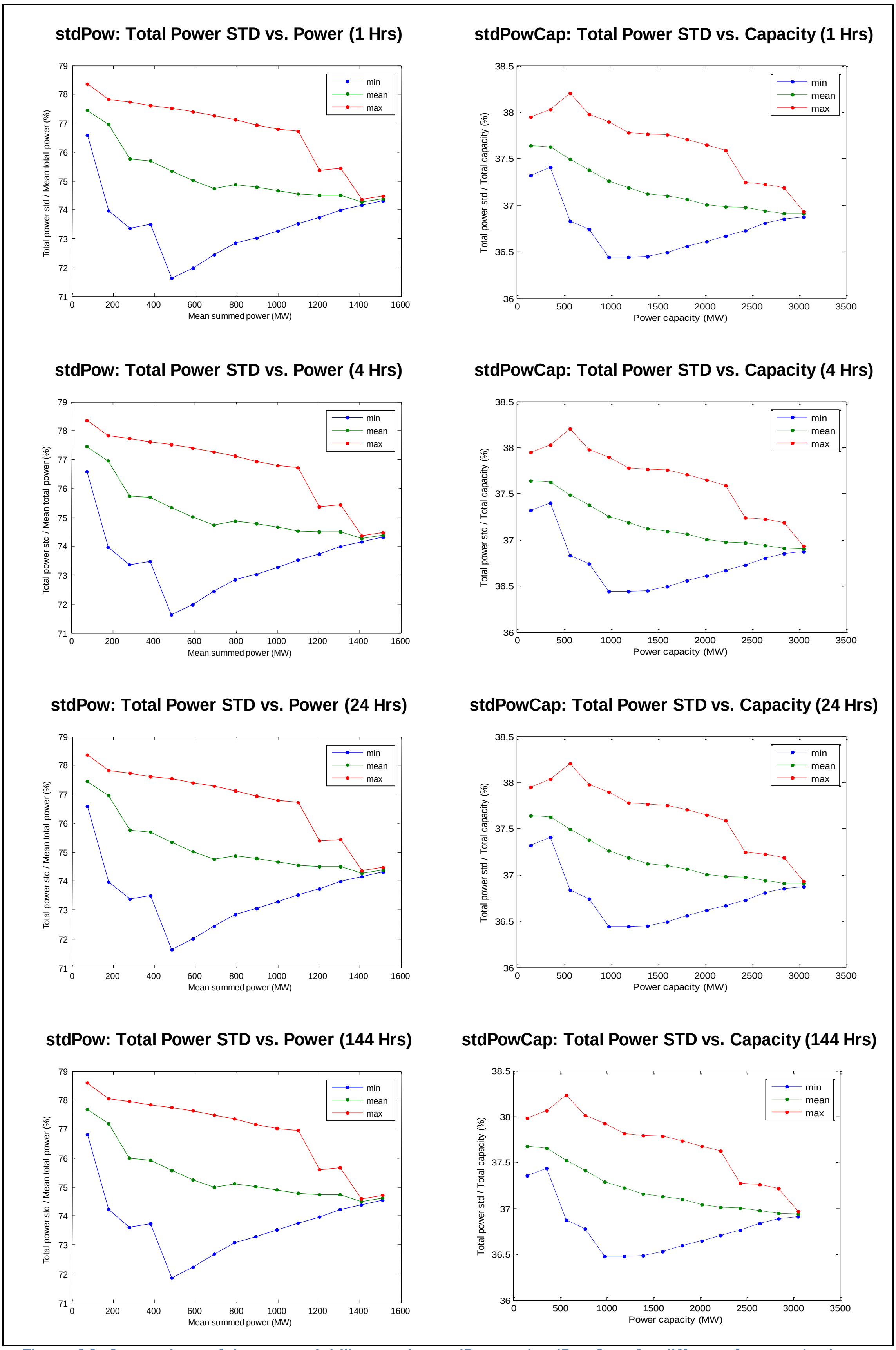


Figure 26. Comparison of the two variability metrics: stdPow and stdPowCap, for different forecast horizons.

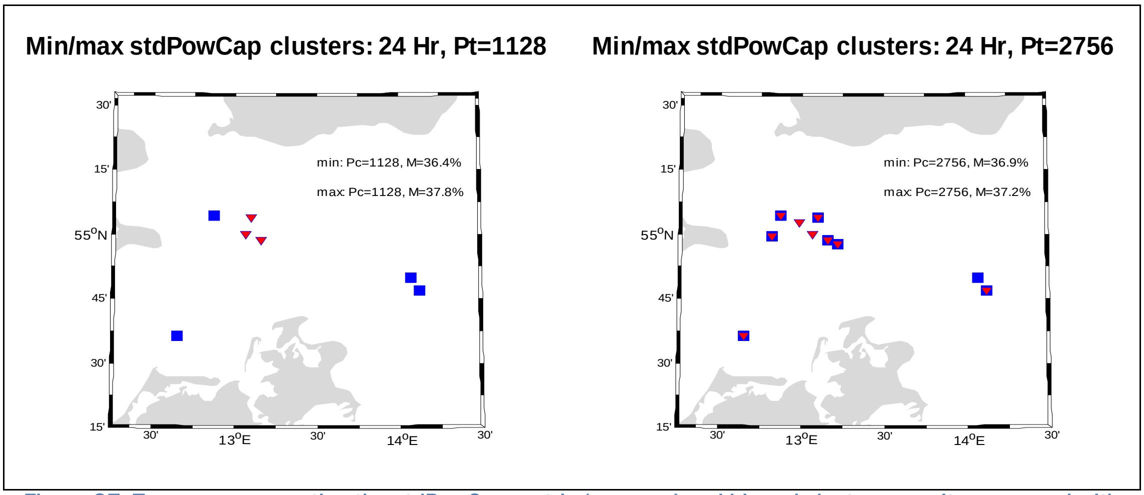


Figure 27. Two maps presenting the stdPowCap metric (summed and binned cluster capacity compared with std/summed Capacity) for 24 hr horizon. The improvement of the metric (left side) is related to the spatially diverse installations.

4.3.5 Forecasting error vs. Variability

It is also no surprise that variability is nearly linearly related to forecasting error, as is shown in the graphs entitled, "Total forecast error vs. Normalized power (* Hrs)". The y axis is the forecasting error in RMS MW and the horizontal axis is the total power std. Those graphics were already introduced in Figure 18 on page 20.

5 CONCLUSIONS

Wind power is characterized by variability and uncertainty, due to the stochastic nature of its prime mover, the wind speed. When wind power penetration reaches higher levels, this variability and uncertainty pose challenges to the secure and reliable operation of the power system because there is (almost) no storage, so at any given time, production should match consumption. This is expected to increase in the case of offshore wind power, where the geographic concentration of wind power means that the smoothening effect will be less pronounced. Therefore, having tools able to simulate wind power time series that capture the variability expected from the given sites would be very useful in the planning phase of offshore wind farms and clusters.

CorWind is a software tool that allows the simulation of wind power time series that have a realistic variability. Furthermore, CorWind can simulate wind power output in different locations, taking into account the spatial correlation between them.

A possible use of the variability module is presented in this report. For any number of future offshore wind farm locations, CorWind can produce wind power time series, aggregated at wind farm level, that can then be used to a) quantify variability indexes, i.e. max, min and std and investigate clustering options and b) use the resulted time series to estimate the predictability of the offshore cluster. The variability indexes can then be used further when optimizing the clustering of wind farms.

The approach to estimate the predictability based on the cluster configuration is to calculate the forecast error of a cluster using a forecaster (trained ANN) for each single wind farm and to calculate the aggregated error for different configurations. Based on these metrics, the user can decide if one configuration is more predictable (for different time horizons: 1, 4, 24 and 144 hours in advance) than the other.

The requirement of estimating the forecastability of clusters for a time horizon of 1 week used for maintenance purposes is fulfilled thanks to the implementation of the GFS NWP model, providing forecasts 144 hr ahead.

The predictability metrics during this experiment were calculated for all possible cluster combinations and then binned to present the best and worst configuration for each bin. This exercise allows understanding the relationship between the variability and predictability and provides -at the same time- an example regarding the possible kind of analysis that can be performed. Nevertheless, the use of the module in the context of EERA-DTOC not necessarily implies that the final user should create all possible cluster combinations, but it is possible to estimate the predictability only for some specific examples.

Based on the described metrics, the uncertainties of the final power output of each configuration can be directly used in WP3.

Regarding economical assessments, the predictability module does not automatically estimate -based on the calculations and metrics- the cost/ benefit function derived from the improvements on the forecast versus the total infrastructure cost, but the results of the module can be integrated in the cost model of the project to quantify the cost of the uncertainties and improvements regarding the total cost of the infrastructure.

Finally, the predictability module generates the required forecast time series required in Task WP2.4 for the analysis of the capabilities of different cluster configuration providing system services.

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